THREE ESSAYS ON THE ADOPTION, IMPACT, AND PATHWAYS OF CLIMATE-SMART AGRICULTURE: AN EX-POST IMPACT EVALUATION OF A NATURAL RESOURCE MANAGEMENT INTERVENTION IN SOUTHERN MALAWI

BY

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DISSERTATION

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ABSTRACT

This dissertation consists of three (3) papers on climate-smart agriculture (CSA) – an increasingly important approach for achieving sustainable development objectives in the face of global climate change and extreme weather events. It advances theoretical and empirical knowledge at the intersection of agricultural development, environmental economics, and natural resource management through a set of analysis of a large USAID-funded intervention in southern Malawi, which promoted CSA in the area. Specifically, it contributes to narrowing the following gaps in the literature: a) lack of conceptual clarity on farm-level CSA practices with highest adoption potential, b) paucity of evidence on the effectiveness of externally supported CSA projects and c) dearth of empirical evidence on specific pathways through which CSA projects generate effects. The dissertation utilizes primary survey data collected from 808 households in five districts across southern Malawi. To obtain plausible estimates of a counterfactual for the CSA intervention, I used rigorous analytical techniques that control for endogeneity and selection bias due to non-random program placement and unobserved heterogeneity. In the first paper, I developed a typology of farm-level CSA practices, which helped to generate and test hypotheses on CSA adoption dynamics in the study area. I then used recursive bivariate probit regression to estimate CSA adoption by CSA practice type (or category). Results showed that the program increased adoption probability by at least 41% and that CSA adoption rates were highest for labor-intensive practices such as installation and maintenance of physical infrastructure like stone bunds and water absorption trenches. Paper 2 used endogenous switching regression to estimate food security impacts of CSA adoption in terms of agricultural yields and household income. I found that on average, CSA adopters obtained yield and household income increases of 90% and 41% respectively. The third paper utilized a double hurdle model with control function to estimate the impact of CSA program participation on agricultural yields, conditional on agroforestry adoption as a CSA impact pathway. The result indicates that CSA program participants that adopted agroforestry saw their yields increase by an average of 31%. In addition to the conceptual and empirical contributions, this dissertation has significant policy implications for sustainable rural development in Malawi and elsewhere in Africa and beyond. For instance, development policies that promote externally funded CSA programs could enhance the adoption of resource-intensive, but higher impacts CSA categories such as agroforestry and physical infrastructure like continuous contour and water absorption trenches, thereby improving environmental conservation and food security in the developing world.

Keywords: Adoption; Agroforestry; Africa; Climate Smart Agriculture; Developing country; Climate financing; Double hurdle; Endogenous switching regression; Evironmental sustainability; Externally funded; Food security; Household; Income; Malawi; recursive bivariate probit; Poverty reduction; Propensity score matching; Yield.

DEDICATION

To Almighty God through my Lord and Savior – Jesus Christ, who has bestowed such blessing upon me as to be counted among the very few to obtain a PhD, and especially for being first in my family lineage to have come this far academically. I therefore will lay it at God's throne (Rev., 4:10-11).

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TABLE OF CONTENTS

ABBREVIATIONS AND ACRONYMS

ADD	Agricultural Development Division
AEDC	Agricultural Extension Development Coordinator
AEDO	Agricultural Extension Development Officer
AIARD	Association for International Agricultural and Rural Development
Borlaug LEAP	Borlaug Leadership Enhancement in Agriculture Program
CGIAR	Consultative Group for International Agricultural Research
CAPI	Computer Assisted Personal Interviewing
CRS	Catholic Relief Services
CSA	Climate-Smart Agriculture
DADO	District Agricultural Development Officer
EPA	Extension Planning Area
FAO	Food and Agriculture Organization
GHG	Green House Gas
GVH	Grouped village headman
IFPRI	International Food Policy Research Institute
IHS4	Integrated Household Survey 4
IPCC	Intergovernmental Panel on Climate Change
LUANR	Lilongwe University of Agriculture and Natural Resources
MRG	Miller Research Group
NGO	Non-Government Organization
NRES	Natural Resources and Environmental Sciences
ODK	Open Data Kit
SANE	Strengthening Agriculture and Nutrition Extension
UBALE	United in Building and Advancing Life's Expectations
UIUC	University of Illinois at Urbana-Champaign
USAID	US Agency for International Development
WALA	Wellness and Agriculture for Life's Advancement

CHAPTER 1:

GENERAL INTRODUCTION AND LITERATURE REVIEW

1.1. AGRICULTURAL AND ENVIRONMENTAL CHALLENGES IN AFRICA

The agricultural and environmental sectors (including natural resources such as forests and vast arable lands) constitute the economic backbone of many countries in Africa. These sectors provide employment opportunities for majority of the rural population and are the main drivers of economic growth throughout the continent (Gebremariam & Tesfaye, 2018; Manda et al., 2017). However, food insecurity and poverty remain high in most countries in Sub-Saharan Africa (SSA), in significant part due to weak natural resource management and difficult climatic conditions, among other factors (Berazneva et al., 2018; Bhargava et al., 2018; FAO, 2016). Such factors have negatively affected agricultural productivity and environmental sustainability. As a result, economic growth in terms of per capita gross domestic product (GDP) has been comparatively sluggish over several decades (Abro et al., 2014; Ampaire et al., 2017; Collier & Dercon, 2014).

Climate change and extreme weather events, such as severe droughts and crop failure—triggers of food insecurity crises—pose further challenges to sustainable development across the continent (Aggarwal et al., 2018; Barrett et al., 2017; Ubilava, 2018). Additionally, heavy reliance on rain-fed agriculture and preponderance of extensive agriculture, makes SSA a region highly vulnerable to climate change and extreme weather shocks (Arslan et al., 2015; Asfaw et al., 2016; Binswanger-Mkhize & Savastano, 2017). For example, the recent El Niño droughts in southern Africa devastated maize yields in the 2015/16 farming seasons and was particularly grievous as it resulted in massive food security crises in the region (Ubilava, 2018; World Bank Malawi Office, 2016; World Food Programme, 2017).

Resource scarcity, particularly in many rural areas of the continent, exacerbates vulnerability to climate change and makes it difficult for communities to implement environmentally sound practices, more generally. Instead, livelihood strategies in some communities depend on destructive practices such as unsustainable charcoal production for the local market (Babulo et al., 2008; Butz, 2013; Jagger & Perez-Heydrich, 2016; Kalipeni & Zulu, 2002), continuous tillage, and other activities that result in forest loss and soil degradation (Butz, 2013; Jagger & Perez-Heydrich, 2016; Kalipeni & Zulu, 2002). Such practices further exacerbate weak agricultural growth, poverty, and food insecurity. Therefore, observers (e.g., Collier and Dercon, 2014; Connolly-Boutin & Smit, 2016; Ubilava, 2018) warn that the current trend of weak socioeconomic growth and development in Africa could become worse unless there are drastic measures to tackle climate change.

In this context, climate-smart agriculture (CSA) is viewed increasingly as a promising approach to tackle the problems of negative socioeconomic outcomes in Africa arising from climate change and extreme weather events. CSA is particularly useful due to the synergy between agriculture and climate change mitigation and adaptation and (FAO, 2016; Jayne et al., 2018; Steward et al., 2018). CSA presents an important strategy to tackle the effects of climate change on agriculture in the continent because it helps to ensure that agriculture proceeds in ways that protect and conserve natural resources (Chandra, Dargusch, et al., 2017; FAO, 2016; Lipper et al., 2014). Moreover, CSA is critical for rural communities who simultaneously depend on agriculture and limited natural resources for their livelihoods (Sommer et al., 2018; Teklewold et al., 2017; van Noordwijk, 2017).

However, despite a number of analyses highlighting the import of CSA for natural resources management and environmental conservation in SSA, precise estimates of the adoption of CSA remain elusive in the sub-continent (Aggarwal et al., 2018; Ampaire et al., 2017; Karlsson et al., 2018). Some authors (e.g., FAO, 2010; Khatri-Chhetri et al., 2017; Lipper et al., 2014) argue that smallholder farmers in the developing world, especially SSA, face binding resource constraints that may constrain them from fully adopting CSA despite the potential benefits of doing so. An important reason is that many CSA practices (such as physical infrastructure like stone bunds and contour trenches) are resource intensive and are thus hard for average smallholder farmers to afford (FAO, 2016; Khatri-Chhetri et al., 2017; Kpadonou et al., 2017).

Therefore, from a climate justice standpoint (Adger et al., 2017; Chandra, McNamara, et al., 2017; Karlsson et al., 2018; Schlosberg, 2013), smallholder farmers in the developing world where government investments in climate adaptation are minimal will require external assistance, such as international aid, to enhance their adoption of CSA interventions. Such interventions may be required in resource-poor contexts to deliver benefits not only to individual smallholders but also provide the wider public goods benefits inherent to CSA (Alisat & Riemer, 2015; Benjamin et al., 2018; Engel & Muller, 2016). Adoption of CSA by a group of farmers within a locality reduces the marginal costs of carbon abatement and downside risks in the ecosystem (Eory et al., 2018; Huang et al., 2015; Huang & Wang, 2018). Moreover, climate adaptation aid, such as that for CSA, can reduce the transaction costs for resource-intensive CSA practices and produce viable societal benefits (Adger et al., 2017; Aggarwal et al., 2018; Agrawal & Lemos, 2015; Kahsay & Hansen, 2016; Weiler et al., 2018).

To that end, the international development community has increased climate financing to developing countries over the past decade with projections estimated at around US$100 billion by 2020 (Dinesh et al., 2017; Donner et al., 2016; Weiler et al., 2018; World Bank, 2015, 2017b). However, despite such increasing climate adaptation financing in tandem with CSA adoption and impact goals, estimates of adoption at smallholder levels in SSA remain low (Gebremariam & Tesfaye, 2018; Senyolo et al., 2018; Steenwerth et al., 2014). Even when some CSA practices like conservation agriculture (CA) have been adopted, their effectiveness remains debatable (e.g., Sommer et al., 2018; Teshome et al., 2016; Thierfelder et al., 2017).

CSA practices are highly diverse across contexts and so adoption estimates are often elusive, especially at the farm-level of smallholders in the developing world (Arslan et al., 2015; Asfaw et al., 2016; Torquebiau et al., 2018). Thus, it is no surprise that analyses of CSA adoption and estimation of adoption impacts are often not generalizable beyond the local context (Chandra et al., 2018; Gebremariam & Tesfaye, 2018; Lipper et al., 2014). Lack of conceptual clarity, in terms of a clearly defined CSA identification framework for an analysis of adoption inhibits adoption estimates across contexts. From a policy and practice perspective, it also makes it hard to identify and promote CSA practices that have highest adoption potential, and to identify the conditions under which such CSA practices could be best adopted. Another consequence of this lack of conceptual clarity is that estimates of the *impacts* of CSA adoption become less comparable across contexts. Finally, such gaps make an understanding of and advancement in scholarship concerning CSA adoption, comparability of adoption, and impacts difficult.

1.2. FOCUS OF THIS DISSERTATION

This dissertation addresses the issues and knowledge gaps discussed above. Specifically, it focuses on answering the following set of questions:

1. *How can CSA practices at the farm level of individual smallholder farmers and communities be better conceptualized to enhance estimates of adoption across contexts for potential comparability of adoption rates?*
2. *What CSA adoption heterogeneity exists, which CSA categories have more adoption potential than others, and under which conditions does the heterogeneity manifest?*
3. *What is the effect of CSA adoption on agricultural yields, income, and overall food security for households?*
4. *Through which pathways does CSA generate effects on food security?*

My dissertation responds to these questions through engagement with key literatures and an empirical case study of a CSA-related natural resources management intervention in southern Malawi. Through a series of analyses of CSA adoption, the impact of adoption, and pathways of impact in the ensuing chapters, my dissertation seeks to narrow the above-mentioned gaps and advance knowledge in this important area of research and policy. The intervention focus is the Wellness and Agriculture for Life Advancement (WALA) program, which the United States Agency for International Development (USAID) funded to promote CSA adoption in southern Malawi from 2009 to 2014.

This study consists of a set of three separate but related research papers, each of which covers a different aspect of the questions posed above. Each paper uses different analytical techniques based on primary survey data that were collected specifically for this enquiry. The first paper relates to CSA adoption, the second paper estimates the impacts of adoption, and the third paper identifies a causal pathway by which the CSA intervention affected food security.

The ensuing core chapters of this dissertation contribute to advancing current knowledge in three main ways. First, they provide conceptual clarity on CSA adoption in the development and testing of a farm-level CSA typology. This enhances an analysis of CSA adoption and impacts of CSA applications at the farm level across diverse contexts, especially in the developing world. Second, they provides empirical evidence of the effectiveness of a major, externally funded CSA intervention in spurring adoption, particularly of CSA practices that have lower adoption probabilities in the absence of external support. Third, the chapters provide evidence of the effect of CSA adoption on food security–related measures: agricultural yields and household income. Finally, the chapters highlight pathways through which CSA affects food security outcomes such as crop yields—a measure of food availability (Campbell et al., 2016; Jaleta et al., 2018; Kassie et al., 2015).

Malawi—the subject of this dissertation—is a country in SSA and, being a tropical country, experiences a single rainy season and a dry season. The two seasons often last from October to April, and May to September, respectively. This rainfall seasonality and a weak irrigation system in the country often limits soil fertility and affects agricultural production, especially in rural communities, which constitute the majority of the country's farming population (Asfaw et al., 2016; Radchenko et al., 2018; Sesmero et al., 2017). These factors together with an increasingly uncertain climate mean that CSA adoption is likely to be of critical import for the rural economy of Malawi.

Moreover, Malawi has a long history of many socioeconomic challenges. These include extremely high rural poverty (Fisher & Kandiwa, 2014; Kalipeni, 1996; National Statistical Office of Malawi, 2017b), high gender disparity in the adoption of agricultural technologies (Mutenje et al., 2016; National Statistical Office of Malawi, 2017b), and low agricultural production outcomes (Coulibaly et al., 2017; Fisher & Lewin, 2013; National Statistical Office of Malawi, 2017a,b).

Increased international focus on climate adaptation and CSA financing in developing countries (Adger et al., 2017; Agrawal & Lemos, 2015; Huang & Wang, 2018; Weiler et al., 2018) has caused Malawi and many countries in SSA to receive significant climate adaptation aid in the past decade (Dinesh et al., 2017; Donner et al., 2016; Weiler et al., 2018). For instance, in the past decade, Malawi has received millions of dollars in financing for many climate-related aid interventions and public-sector programs, such as the well-known government-subsidized Farm Input Subsidy Program (FISP).

Climate financing in Malawi mostly aims to reduce high environmental degradation and food insecurity, among other goals (Asfaw et al., 2016; Jayne et al., 2018; Poppy et al., 2014; Weiler et al., 2018). This is particularly crucial in the southern region, which has had prolonged environmental degradation arising from long-term resource depletion due to high population density and other factors (Kalipeni & Zulu, 2002; National Statistical Office of Malawi, 2017a; Zulu, 2008).

USAID is among the largest donors supporting rural development efforts in southern Malawi. For instance, from 2009 to 2014, it funded WALA, a US$86 million development aid project, in an effort to curb long-term poverty and food insecurity stemming from long-term resource depletion and difficult environmental factors in the region (Reichert, 2014; Soroko et al., 2018). WALA's goal was to improve natural resources and environmental management, resulting in higher agricultural yields among smallholder farmers across eight districts of southern Malawi (Figure 1.1 and Appendix B) (Soroko et al., 2018).

WALA had three components including the following: (1). Households' nutritional improvement through, for example, mother and child nutrition and health training; (2). Socioeconomic empowerment of communities and capacity building against different forms of disaster risks for marginalized groups (Reichert, 2014; Soroko et al., 2018; Verduijn, Downen, Walters, & Wyeth, 2014); and (3). Agricultural development and food security through natural resource management activities such as soil and water conservation practices (e.g., agroforestry, contour trenches, stone bunds, and water absorption trenches).

This dissertation focuses on the third component of WALA because of its articulation of climate adaptation and natural resources management practices. Thus, I henceforth refer to WALA's third component as "CSA" because it includes many practices that constitute CSA, as this section shows. WALA did not refer to these practices as "CSA" during the program implementation period (2009 through 2014) itself, but all the practices it implemented closely align with CSA and project staff now consider it to be a CSA intervention. Therefore, I adopt the broad terminology of CSA for WALA's soil and water conservation practices targeted toward reducing environmental degradation and increasing food security in the project area.

The remainder of this introduction is structured as follows. The next section provides a succinct review of the extant literature on CSA. Next, I provide detail on the study context and CSA intervention in Section 1.4. Section 1.5 describes the overall methodology in terms of sample selection for the data. This chapter concludes with a preview of each of the core chapters in terms of the broad goal, analytical technique employed, and their outcomes.

1.3. CLIMATE-SMART AGRICULTURE (CSA) FOR SUSTAINABLE AGRICULTURE IN SUB-SAHARAN AFRICA

CSA is increasingly popular as a solution to agricultural development challenges in developing countries, including those in SSA. Two publications of the Food and Agriculture Organization of the United Nations (FAO)—*Climate-Smart Agriculture* (FAO, 2010) and *Climate-Smart Agriculture Sourcebook* (FAO, 2013) helped propel interest in the concept of CSA. The original FAO definition considers CSA as an approach which "sustainably increases productivity and resilience (adaptation), reduces/removes GHGs (mitigation), and enhances achievement of national food security and development goals" (FAO, 2010, p. ii; FAO, 2013).

The FAO CSA definition is highly functional with a descriptive focus. Scholarship around the CSA concept has thus emphasized the description of what CSA does, which is why, for example, Jayne et al. (2018) find that CSA is still "not clearly defined in the academic literature" (p. 253). The notion that CSA is more functionally descriptive than definitive is becoming well established in the extant literature and provides a major impetus for this dissertation research. As such, I build from a range of key studies to establish the theoretical and empirical basis for this research. One such study is Lipper et al. (2014), which accordingly state that "CSA emphasizes agricultural systems that utilize ecosystem services to support productivity, adaptation, and mitigation" (p. 1069). Further, Lipper et al. (2014) argue that CSA is relevant because "enhancing soil quality can generate production, adaptation and mitigation benefits by regulating carbon, oxygen, and plant nutrient cycles, leading to enhanced resilience to drought and flooding, and to carbon sequestration" (p. 1069). Similarly, Thierfelder et al. (2017) state that CSA practices are bound by a common thread of three functions: adaptation, mitigation, and agricultural productivity (in terms of yields and farm income). Some examples of CSA approaches and practices identified in the study by Lipper et al. (2014) include:

- integrated crop, livestock, aquaculture, and agroforestry systems;
- improved pest, water, and nutrient management;
- landscape approaches;
- improved grassland and forestry management;
- integrating trees into agricultural systems;
- restoring degraded lands; and
- improving the efficiency of water and nitrogen fertilizer use.

CSA is an approach that applies context-specific techniques or practices (Chandra, Dargusch, et al., 2017; FAO, 2016; Jayne et al., 2018). Additionally, CSA leverages the cooperation of various stakeholders, including farmers, development practitioners, policymakers, and researchers toward the triple goals of adaptation, mitigation, and food security across diverse contexts (Lipper et al., 2014; Steenwerth et al., 2014; Torquebiau et al., 2018). As such, different stakeholders can achieve multiple objectives across contexts without having to do the same things in every place to achieve the same set of outputs (Brandt et al., 2017; Lipper et al., 2014; Schaafsma et al., 2018).

These descriptions of CSA suggest that it encompasses several previous agronomic and environmental management practices. Examples include: (1) agroforestry, which has become increasingly important in the literature (e.g., Andres et al., 2018; Coulibaly et al., 2017; Garrity et al., 2010; Miller et al., 2017); (2) conservation agriculture – another vital subject (e.g., Sommer et al., 2018; Steward et al., 2018; Thierfelder et al., 2017); and (3) integrated soil fertility management (e.g., Sommer et al., 2018; Teklewold et al., 2017; van Noordwijk, 2017).

CSA also includes watershed development activities such as contour trenches, stone bunds, terraces across steep slopes, and other forms of catchment management. These techniques reduce soil erosion, improve the percolation and retention of water across croplands, and enhance agricultural productivity in drylands (Alemayehu et al., 2009; Branca et al., 2011; Fu et al., 2012; Schaafsma et al., 2018; Sommer et al., 2018).

Watersheds comprise of catchment areas in a landscape that drains water toward a common spot, which makes them crucial in agricultural systems, natural resource planning, soil fertility, and water conservation (Kerr, 2002). Thus, watershed development, as promoted through the WALA project, has become a vital approach to managing groundwater resources to support agricultural activities and provision of ecosystems services, especially in areas highly vulnerable to climate change impacts (Burnett & Wada, 2014; Gelagay & Minale, 2016; Kerr, 2002). Such an approach usually emphasizes community-level effort to build the institutional capacity of rural communities (Brandt et al., 2017; Chandra, Dargusch, et al., 2017; Chandra, McNamara, et al., 2017; Chandra et al., 2018).

The growing literature on CSA generally falls into three broad strands. The policy framework literature advocates for CSA prioritization and financing in development priorities and is arguably the most visible (Andrieu et al., 2017; Jayne et al., 2018; Lipper et al., 2014). Prominent actors advancing this strand of the literature include international development organization such as FAO, World Bank, and International Fund for Agricultural Development (IFAD), among others (Dinesh et al., 2017; Lipper et al., 2014; Sain et al., 2017). This strand includes many studies arguing for higher CSA financing priorities in national and international development programs (e.g., FAO, 2016; Mwongera et al., 2017; Weiler et al., 2018). For instance, *The State of Food and Agriculture: Climate Change, Agriculture and Food Security* (FAO, 2016) presents several policy recommendations for the integration of climate adaptation, financing, and targeting of CSA goals to enhance food security and environmental sustainability.

The Intergovernmental Panel on Climate Change (IPCC) has also weighed in on this subject; for example, in its *5th Assessment Report* (IPCC, 2014), which suggested the need for concerted global efforts to reduce catastrophic consequences of climate-related shocks in the developing world. In a recent empirical assessment of adaptation aid allocation, Weiler et al. (2018) find that general development and climate adaptation are interwoven, and that such phenomena might not be in the best interest of the climate policy view, because it makes it hard to differentiate the effect of climate adaptation aid from general development aid.

The second strand of the CSA literature focuses on dynamic analyses of the effects of climate change. Examples include modeling (Chalise & Naranpanawa, 2016; Turner et al., 2016; Ubilava, 2018), forecasting or projections (Kahsay & Hansen, 2016; Ubilava, 2018), and scenario analyses (Kim et al., 2017; Lopez-Ridaura et al., 2018; Rosen & Guenther, 2015). For instance, Ubilava (2018) in southern Africa uses time-series data to model regional agricultural price fluctuations as a result of cyclical weather fluctuations such as sea surface temperature (SST) and El Niño drought oscillations. He finds substantial heterogeneity in the price variations caused by drought and SST changes in the region. Similarly, in a series of farm household food security scenario analyses based on differing farming systems, Lopez-Ridaura et al. (2018) in East India find heterogeneous effects on potential food security across farming systems and types.

The third strand focuses on empirical analyses of the adoption and impacts of CSA on food security through agricultural yields, household income, and other welfare measures such as reduction of poverty headcount. For example, the meta-analysis by Steward et al. (2018) found that maize yields in conservation agriculture systems perform very effectively under drought and extreme heat conditions, thus highlighting the import of CSA through conservation agriculture.

This strand includes a rapidly growing number of country-specific analyses of the adoption of diverse CSA types, such as soil and water conservation practices, and the resulting impacts on food security and other welfare outcomes (e.g., Arslan et al., 2015; Asfaw et al., 2016; Sommer et al., 2018).

Review of the extant literature on CSA uncovered three important information gaps, which the ensuing chapters of this dissertation address. First, a surprising lack of conceptual clarity of CSA practices at the farm household and community levels with the highest adoption potential is a major gap. To address this gap, I developed a farm household–level CSA typology that could enhance an analysis of CSA adoption at the farm household and community levels for smallholder farmers in Sub-Saharan Africa, taking southern Malawi as a case study. Most CSA adoption studies (e.g., Arslan et al., 2015; Kpadonou et al., 2017; Lopez-Ridaura et al., 2018; Schaafsma et al., 2018; Senyolo et al., 2018) do not utilize a CSA typology in their analyses of CSA adoption and associated impacts, nor do they explicitly show which CSA practices have highest adoption potentials. Because CSA practices are numerous across scales such as national, institutional, and farm levels (Brandt et al., 2017; Chandra, Dargusch, et al., 2017; D'Souza & Mishra, 2018; FAO, 2016), the advancement of a typology for analyzing their adoption and impacts enhances a conceptual clarity of CSA in general, and at the farm household level of smallholders in particular. It also enhances comparability of impacts of CSA adoption across contexts.

Another gap is a dearth of empirical evidence of the effectiveness of externally supported CSA interventions in Sub-Saharan Africa despite a rising global investment in CSA and other climate adaptation strategies. For instance, studies show that in the past decade, climate financing has increased dramatically in tandem with the promotion of, and research on CSA-related activities (Dinesh et al., 2017; Donner et al., 2016; Weiler et al., 2018). Such global investment is expected to climb to about US$100 billion by 2020 (Dinesh et al., 2017; World Bank, 2017a), yet there are no prior analyses of externally supported CSA projects in terms of their success in enhancing CSA adoption or associated impacts of adoption. Such analyses are important in determining the effectiveness (or the lack thereof) of external CSA interventions, and their potential for affecting development outcomes.

Third, there is a lack of analyses of CSA impact pathways in the extant literature. Several studies in closely related fields such as ecosystems services and protected areas (e.g., Ferraro & Hanauer, 2014, 2015; Fish et al., 2016) entail analyses of pathways for the identification of causal impacts on various outcomes. However, the current dearth of analyses on CSA impact pathways limits a comprehensive understanding of CSA impacts at various levels including the farm household and plot levels.

1.4. COUNTRY CONTEXT AND STUDY BACKGROUND

Malawi is one of the poorest countries in SSA (World Bank, 2017b). It has a low per capita gross national income (GNI) of US$340 compared to similar countries in southern Africa such as Zimbabwe, with GNI of US$860, and Madagascar, with GNI of US$420 (World Bank, 2017b). Extreme poverty is pervasive in the country with recent estimates of national poverty (in terms of the proportion of households living below the US$1.90 per day international poverty line) in 2016 and 2017 at 69.8% and 69.4%, respectively (World Bank Malawi Office, 2017).

Maize is the staple crop in Malawi, grown by more than 70% of the rural population, followed by tobacco, which is the main export crop (Radchenko et al., 2018; Schaafsma et al., 2018; Sesmero et al., 2017). With frequent environmental shocks including frequent dry spells, Malawi's biophysical and socioeconomic conditions present challenging food security situations for the bulk of its citizens, especially in rural areas (Mussa, 2015; Radchenko et al., 2018; Sesmero et al., 2017). For instance, recent food insecurity estimates from the country's Fourth Integrated Household Survey (IHS4) show that national food insecurity stands at 61% (National Statistical Office of Malawi, 2017b). There are variations across regions, with higher estimates (63%) for the southern region, compared to 61% in the northern region and 58% in the central region (National Statistical Office of Malawi, 2017b).

Moreover, sustained environmental degradation exacerbates food security problems in Malawi, through persistent food security risks given that the country is heavily dependent on maize production—the staple crop, which is highly sensitive to droughts. Such risks have taken a toll on the national budget over time; as recently as 2015, the El Niño drought hit the country and caused debilitating crop losses (Ubilava, 2018; World Bank Malawi Office, 2016; World Food Programme, 2016, 2017). The World Bank Malawi Office (2017) Post Disaster Needs Assessment conducted in 2015 concluded that flooding following the El Niño drought resulted in damages and losses of around US$335 million, or approximately 5.2% GDP. In part due to such losses and challenges, the food insecurity situation in Malawi has attracted many international programs over the last four decades, but especially in the recent past, including a variety of agricultural subsidies offered through the government of Malawi (Jayne et al., 2018; Koppmair et al., 2017; Ricker-Gilbert et al., 2011).

Malawi has also long experienced population growth, particularly in the last four decades, with higher population densities in the southern region, thereby affecting natural resource depletion and poverty in the south compared to elsewhere in the country (Kalipeni, 1996; Mazunda & Shively, 2015; National Statistical Office of Malawi, 2017a; Peters, 2006;

Poppy et al., 2014). The average fertility rate in 2017 was 4.4 (National Statistical Office of Malawi, 2017a), but there is considerable heterogeneity in fertility rates across districts, with the highest figures recorded for southern districts compared to districts in other regions. For example, two districts in the far south—Chikwawa and Nsanje—have population densities of 5.6 and 5.7, respectively, compared to Karonga and Chitipa in the far north, accounting for 4.3 and 4.5, respectively (National Statistical Office of Malawi, 2017a).

Concerns about population growth and environmental degradation have, in turn, given rise to a range of climate-related interventions in Malawi stretching back to pre-colonial period (Kalinga & Pike, 1965; Phiri et al., 2012). The logic of these interventions hinges on the need to address conservation, agricultural development and food security goals in the face of challenging biophysical conditions such as periodic droughts (Kalinga & Pike, 1965; Phiri et al., 2012; Weiler et al., 2018), though scholars have also noted how such interventions have formed a means of asserting or maintaining political control (Beinart, 2007; Morris, 2016). Southern Malawi, the geographic region that is the focus of this dissertation, has been an area of special emphasis in these programs due to high poverty, environmental degradation, and food insecurity in the face of harsh climatic stress (National Statistical Office of Malawi, 2017b; Soroko et al., 2018; World Bank Malawi Office, 2016; Zulu, 2008).

The eight districts that WALA selected have a vulnerability to climatic fluctuations and extreme weather events, with concomitant effects on food security (Verduijn et al., 2014). They also have prolonged environmental degradation from long-term depletion of forest biomass for fuelwood and charcoal, and a system of slash-and-burn agriculture; thus, the bulk of their rural communities dwell and rely on marginal lands (Fisher & Lewin, 2013; National Statistical Office of Malawi, 2017a; Verduijn et al., 2014).

CSA was a centerpiece of WALA and utilized considerable resources. Although not precisely stated in its final evaluation reports, discussions with staff from WALA and Catholic Relief Services (CRS), one of the implementing agencies of the project, during fieldwork suggest that the project spent an estimated 40% of its total project costs on CSA activities. For instance, post-WALA qualitative reports suggest that WALA spent about US$2.2 million per district on physical infrastructure in the form of food for asset over the project period (Reichert, 2014; Verduijn et al., 2014). Food for assets is described in Section 1.5.

The WALA project is important as a case study for CSA in Malawi because it is one of the largest externally funded CSA investments in the past decade, with CSA-related activities at the farm level as a clear development aid target in Malawi. Thus, it could shed light on similar CSA-related interventions elsewhere in Malawi and beyond in terms of adoption, impacts, and pathways of program participation outcomes.

This dissertation research covered five of the eight districts in which WALA operated (Figure 1.1). These districts include (1) Balaka, (2) Chikawa, (3) Nsanje, (4) Thyolo, and (5) Zomba. The five districts were selected for several reasons. First, they are among the most vulnerable in southern Malawi, being prone to frequent environmental shocks with almost identical magnitudes. Thus, because the data for this dissertation was collected in 2016 during the El Niño drought, it would make sense to visit the farming communities there to examine the impact of WALA, which had ended two years prior. In such a situation, we are more likely to estimate the true counterfactual than if we went to a set of districts that did not have identical levels of shock. Moreover, we went to these districts because three of them—Chikwawa, Nsanje, and Zomba—were among the main districts where a follow-up US$60 million USAID project known as United in Building and Advancing Life’s Expectations (UBALE) was underway with

CRS as its lead implementing agency, as it had been with the WALA project. Balaka and Thyolo were not part of the follow-up project. Thus, the data could show variation in adoption and impacts by controlling for UBALE in the respective regression estimates in this dissertation. In each district, we use households as the unit of analysis. We use district dummies to control for variations at district levels.

In Malawi, the following local government administrative structure provides agricultural service delivery in the rural communities: In every district, there is a District Agricultural Development Office (DADO), which supervises several Agricultural Extension Development Coordinators (AEDCs). The AEDCs work within blocks known as Extension Planning Areas (EPAs). The EPAs consist of several local agricultural municipalities known as Traditional Authorities (TAs), which further consist of several village pools usually under the leadership of a local village head leader known as a Grouped Village Headman (GVH). Thus, in every EPA, the AEDC supervises a group of field extension agents known as Agricultural Extension Development Officers (AEDOs) who work with farmers across a number of GVHs. Such nuanced arrangement implies that technology diffusion can easily occur among farmers across village lines. Therefore, Section 1.5, which explains the WALA intervention, rests on this important background information. It henceforth must be considered in the interpretation.

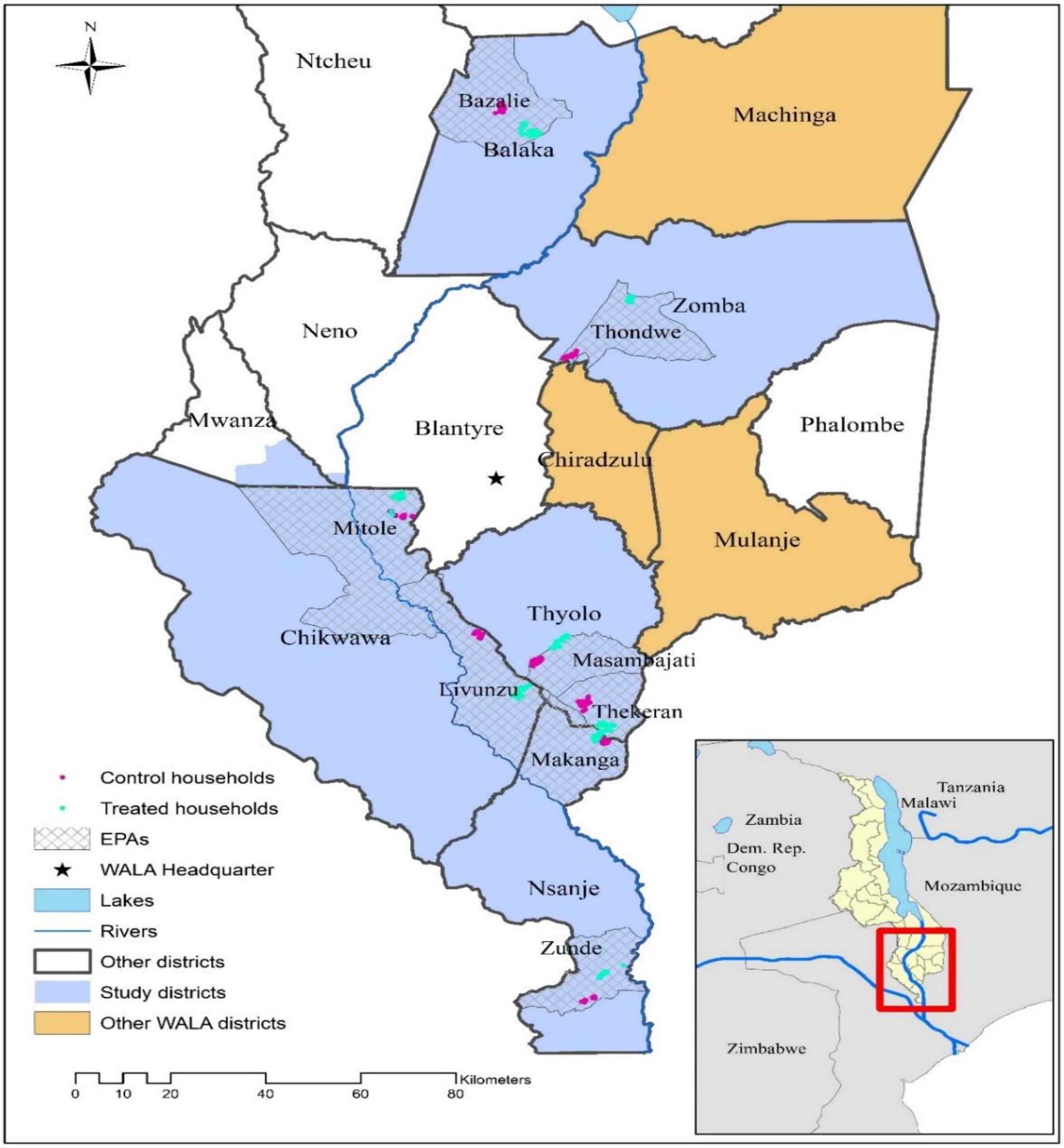

Figure 1.1: Treated and control households within districts

1.5. DESCRIPTION OF THE WALA PROJECT AND ITS CSA APPROACH

The WALA project was a US$86 million program with the goal of achieving improved food security for about 215,000 chronically food insecure households across the project intervention area, which included eight districts (see Figure 1.1). Moreover, a consortium of eight non-government organizations (NGOs), led by CRS,[1] implemented WALA in collaboration with the Ministry of Agriculture of Malawi. Appendix B shows the WALA districts and the corresponding institutions that implemented CSA activities in those districts as part of the WALA consortium. Appendix B also shows the overall operation of WALA in terms of its strategic objectives, project components, target beneficiaries, the implementation levels (in terms how the project reached households) at the GVH or community level in line with Malawi's local government system, and the key activities.

WALA's implementation focused on three strategic objectives:

1. Capacity building of vulnerable households through behavior change approaches, including appropriate nutritional practices to ameliorate malnutrition at the household level.
2. Human and community development activities. Such activities include village savings and loans associations (VSLAs) among beneficiary communities.
3. Natural resource management in watershed development including agroforestry and the installation and maintenance of physical infrastructure such as stone bunds, contour trenches, and check dams.

Although watershed development is not new, the contemporary version of the concept, with roots particularly in India (Glendenning et al., 2012; Goel & Kumar, 2005; Hope, 2007; Pradhan & Ranjan, 2016; Raha et al., 2013) is recent in southern Malawi. From a research perspective, prior studies of watershed development differ from the present study in that they do

[1] The other implementing agencies include World Vision, Africare, Save the Children, Emmanuel International, Total Land Care, Project Concern International, and Chikwawa Diocese (see Appendix B).

not frame watershed development in the context of CSA, nor do they examine the effectiveness of externally supported CSA interventions. In particular, I am not aware of any quantitative evaluation of CSA adoption and impacts through watershed development in southern Malawi.

Note that WALA's implementation did not categorically refer to watershed development as CSA. However, as discussed above and gleaned from the literature review, CSA encompasses all the practices that WALA promoted under its watershed development intervention. Therefore, based on the above discussion of CSA definition and description, this dissertation operationalizes the term *CSA* to mean all of WALA's watershed development activities. WALA implemented these activities to reduce environmental degradation and food insecurity across the project area as discussed above. Hence, it makes sense to call them CSA. Table B3 in the General Appendices provides a description of these CSA practices under WALA.

This dissertation focuses on the third component of WALA as listed above and builds the analyses on its core practices as part of CSA. It estimates the effects of the CSA program under WALA on the adoption of CSA practices among smallholder farmers in southern Malawi, and the resulting effects on food security through maize yields and household income. Since its completion in 2014, the WALA project has not undergone a robust summative evaluation.

The communities selected for participation in the CSA intervention under WALA are those that the project deemed most vulnerable to food insecurity. They lived in areas with typically steep slopes, which make water capture and retention difficult. Such lands are also prone to soil degradation due to long-term erosion (Reichert, 2014; Verduijn et al., 2014).

WALA's CSA implementation primarily involved the active participation of local community members as agents of change whose participation helped to disseminate the CSA technology in the target communities. In particular, WALA combined the services of government extension workers (generally from the Ministry of Agriculture) and community agents who facilitated the technology transfer process within their communities. Thus, WALA comprised a typical blend of the traditional technology transfer (also known as diffusion or government-driven) extension system, and the participatory or demand-driven extension service delivery (Davis, 2008; Davis et al., 2012; Ragasa & Mazunda, 2018).

Participation in the CSA intervention consisted of individual households and community members engaging with WALA to rehabilitate watersheds or catchments as defined above in their respective communities with appropriate CSA practices. Various kinds of CSA practices were applied at different catchments in the project communities (Reichert, 2014). For instance, check dams were often applied in heavy gullies, while afforestation and agroforestry (henceforth, agroforestry) was promoted in almost every community so farmers could plant trees on catchments as well as on their farms even if they are on flat land. To that end, WALA collaborated with the Division of Forestry of the Ministry of Agriculture to facilitate distribution of seeds and seedlings of major agroforestry trees (Reichert, 2014; Verduijn et al., 2014).

The participatory extension approach WALA used to deliver CSA innovations began with identifying farmer extension facilitators or FEFs (also called farmer extension volunteers). These FEFs were farmers themselves, with some education, and they enjoyed considerable respect in the program's target communities in which they resided. They received technical training and logistical support in the form of a bicycle and work supplies. Depending on their location, some of the FEFs received an allowance for their operations and bicycle maintenance; some received a volunteer stipend, while others received no cash support. The FEFs were responsible for transferring CSA knowledge and skills to designated lead farmers (often nominated by the farmers within each village). Each lead farmer worked with one group of about

20 farmers. Lead farmers received training and, in turn, passed on their knowledge to those in their farmers' group through bi-weekly meetings and on-farm visits.

During community-level CSA work, WALA provided "Food for Asset" (FFA[2]) to each participating household albeit they were largely volunteering their time for the community work and learning the CSA skills, especially regarding the earthen infrastructures. The FFA consisted of 4 liters of vegetable oil, and 15kg of pinto beans (Reichert, 2014). WALA offered no other forms of cash transfers in the CSA intervention. Therefore, participation in the intervention was a self-selection process, which precluded random assignment. Figure 1.2 provides an illustration of how WALA reached individual households in the project area.

WALA's evaluation report (Verduijn et al., 2014) indicates that by December 2011, the project had recruited 253 FEFs and facilitated the establishment of about 6,000 farmers' groups involving 116,175 farmers. At that time, the average number of farmers supported indirectly by an FEF was around 460 across the program, ranging from around 230 farmers to a high of over 980 farmers per FEF (Verduijn et al., 2014). Moreover, an end line qualitative assessment (Reichert, 2014) suggested that most communities perceived the CSA intervention as effective and useful for their livelihood improvement. However, no rigorous quantitative analysis exists about the effect of WALA's CSA intervention on the adoption of CSA and associated impacts among the target communities. Conducting such an independent impact evaluation is therefore an important contribution of this dissertation research.

[2] Also known as "food for work" (FFW).

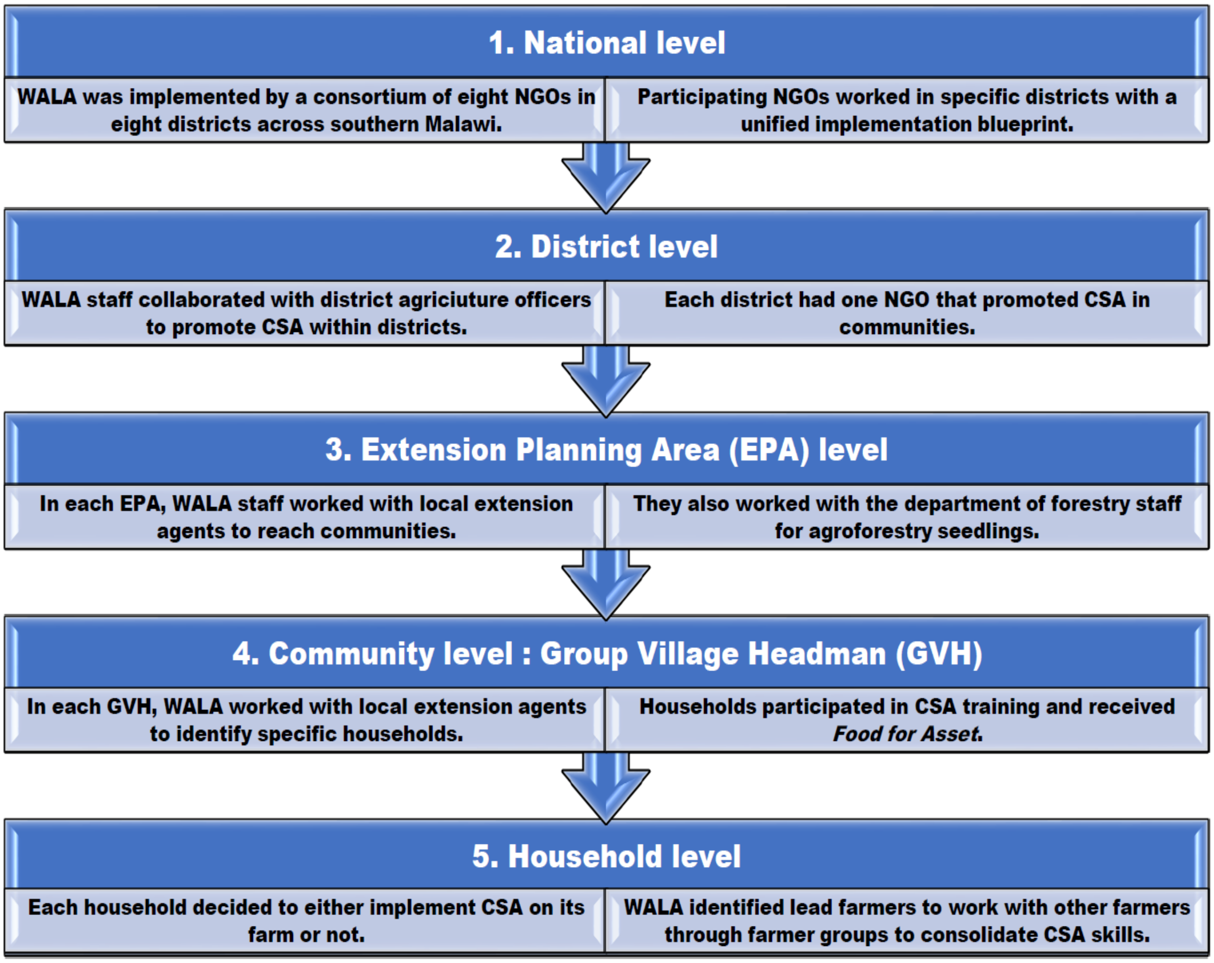

Figure 1.2: Flowchart depicting the interactions of WALA with farmers

1.6. GENERAL DESCRIPTION OF RESEARCH METHODOLOGY AND DATA

This dissertation entails three papers that analyze CSA adoption, impacts of adoption, and a pathway for the impact of the CSA intervention. These papers constitute the second, third, and fourth chapters, respectively. The first paper develops a CSA typology based on a thorough review of the extant literature. Thereafter, the typology and its underlying literature are used to generate and test relevant hypotheses. The empirical applications are based on the CSA intervention under the WALA project as described above and in Appendix B. It constitutes the case study for testing the hypotheses in the typology as well as highlighting the impacts of CSA adoption on agricultural yields and household income.

Southern Malawi is the research setting for this dissertation, and data come from the WALA implementation area. My research focuses on the CSA intervention areas—GVHs organized around watersheds. It applies multistage household-level, plot-level, and community key informant interviews (data) as follows. First, households' socioeconomic data was collected via a survey as the main dataset using 808 households based on proportional sampling per size of GVHs (in terms of the reported number of households in the GVH). Preliminary fieldwork was conducted in November to December 2015 with a more in-depth fieldwork carried out from July to September 2016. During fieldwork, preliminary meetings were held with key informants in each GVH to determine the number of households in the GVH who participated in the CSA intervention under WALA.

Subsequently, random sampling of 15% of the reported number of households was done in each of the GVHs. Sampling proportional to size is a widely used survey method in empirical studies similar to my research setting. Examples include Davis et al. (2012) in East Africa, Coulibaly et al. (2017) in Malawi, and Manda et al. (2017) in Zambia. In addition to household socioeconomic data, we collected plot-level data (Figure 1.3) from each sampled household by visiting one plot per household and observing the plot to identify the existence and extent of any CSA practice. We chose the main agricultural plot of the households. Moreover, we used maize as the main crop because it the main staple for Malawi. Therefore, its productivity is critical for household food security in the country (Kassie et al., 2015).

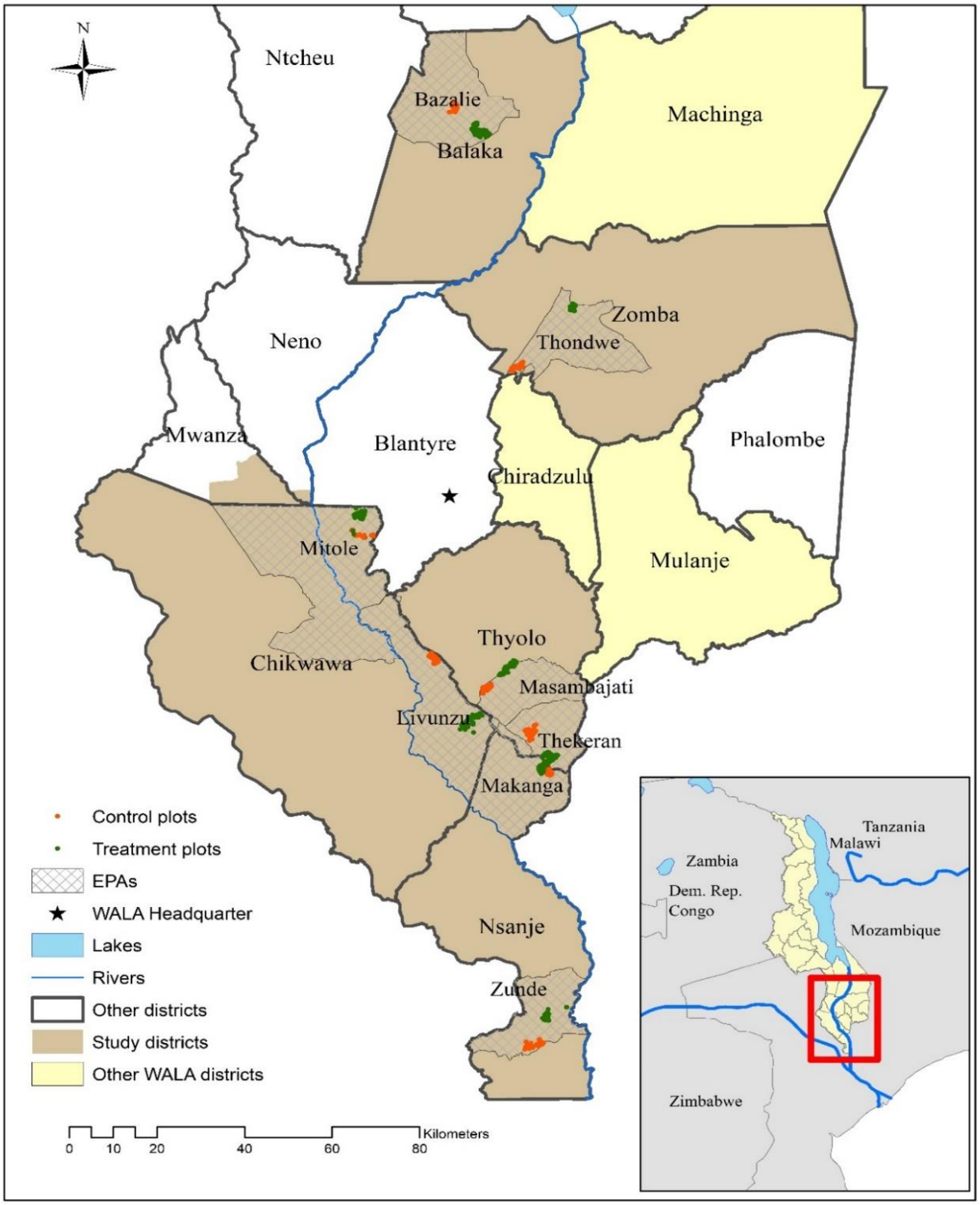

Figure 1.3: Map of treated and control plots within districts

Moreover, we identified CSA practices at the community watersheds and their potential proximity to farmers' plots in terms of distance (in kilometers). Finally, we used state-of-the-art econometric approaches in all the analytical analyses in the ensuing papers that make up Chapters 2–4. Chapter 5 summarizes the results and draws conclusions.

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CHAPTER 2:

UNDERSTANDING FARM-LEVEL ADOPTION OF CLIMATE-SMART AGRICULTURE: A TYPOLOGY WITH EMPIRICAL EVIDENCE FROM SOUTHERN MALAWI[3]

ABSTRACT

Climate-smart agriculture (CSA) is an increasingly important approach to advance rural development and environmental sustainability goals in developing countries. Over the past decade, the international community has committed billions of dollars to support various practices under the banner of CSA. Despite this effort, however, the adoption rate of CSA remains low in many contexts. Lack of conceptual clarity about the range of potential farm-level CSA practices impedes understanding of CSA adoption. It also hinders efforts to promote CSA effectively. Here we develop a typology of CSA practices at farm level to facilitate analyses of CSA adoption. The typology consists of five main categories, organized from least to most labor and capital intensive: (1) residue addition, (2) non-woody plant cultivation, (3) assisted regeneration, (4) woody plant cultivation, and (5) infrastructure construction and maintenance. A sixth category includes a mix of different measures. Based on the typology and the literature underlying it, we generate and test hypotheses about CSA adoption under a large aid-funded CSA program in southern Malawi. We analyze primary household survey data using recursive bivariate probit regression and propensity score matching to estimate the causal effect of program participation on CSA adoption across CSA categories. We find positive and statistically significant effects of program participation on CSA adoption generally, with the strongest effects

[3] This chapter is in revision for submission to a journal.

for adoption within resource-intensive CSA categories such as physical infrastructure and woody plants. Our results demonstrate the potential for wider application of the typology to build knowledge of the effectiveness of CSA promotion efforts across different social and environmental contexts. This research also suggests the importance of external support for enduring adoption of more labor- and resource-intensive CSA practices among rural households and communities in Malawi and elsewhere in the developing world.

Keywords: climate change adaptation, climate-smart agriculture, climate finance, diffusion of innovation, farm household behavior, Malawi

2.1 INTRODUCTION

Climate change and extreme weather events pose major challenges to food security and other international development goals (FAO, IFAD, UNICEF, WFP, & WHO, 2017; World Economic Forum, 2018). The number of undernourished people across the world is estimated to have increased from 777 million in 2015 to 815 million in 2016, with the bulk of this population living in developing countries vulnerable to extreme weather shocks (FAO et al., 2017). In Southern Africa, El Niño–related droughts in recent years have exacerbated food insecurity through low productivity and price effects (Ubilava, 2018). There is therefore an urgent need for adaptation measures to address these climate challenges in the region and across the continent, especially in poor rural areas where livelihoods rely predominantly on rain-fed agriculture and natural resources such as forests (Sommer, Paul, Mukalama, & Kihara, 2018; Teklewold, Mekonnen, Kohlin, & Di Falco, 2017; van Noordwijk, 2017).

In this context, climate-smart agriculture (CSA) is viewed as an increasingly important strategy to not only increase food security but also enhance adaptation to climate change and reduce carbon emissions (FAO, 2010; Lipper et al., 2014; Torquebiau, Rosenzweig, Chatrchyan, Andrieu, & Khosla, 2018). CSA consists of environmentally friendly and economically viable practices designed to advance this "triple win" (FAO, 2013). CSA practices range widely from agroforestry (Blaser et al., 2018; Mbow et al., 2014) to installation and maintenance of physical infrastructure such as contour trenching (Kpadonou et al., 2017; Nyasimi et al., 2017). It also spans multiple scales from individual plots of land (Paustian et al., 2016; Teklewold et al., 2017) to national-level policies (FAO, 2016; Torquebiau et al., 2018).

CSA is well suited for households that rely predominantly on rain-fed agriculture, such as dryland areas in Africa and other world regions. Despite its potential benefits, however, smallholder farmers in the developing world may not be able to afford the high costs of CSA adoption in many cases (Khatri-Chhetri, Aggarwal, Joshi, and Vyas, 2017; Lipper et al., 2014). Some CSA practices (e.g., relating to physical infrastructure) are especially resource intensive and may therefore be particularly difficult for the average smallholder farmer to adopt or retain (Khatri-Chhetri et al., 2017; Kpadonou et al., 2017).

Global funding for climate adaptation strategies, including CSA, has increased dramatically over the past decade (Dinesh et al., 2017). Such investment is expected to reach $100 billion by 2020 (Dinesh et al., 2017; World Bank, 2017). Despite this effort, CSA adoption rates remain low in developing countries, particularly in Sub-Saharan Africa (Khatri-Chhetri et al., 2017; Kpadonou et al., 2017; Mwongera et al., 2017). Understanding the reasons for low adoption rates and identifying means to overcome them to enable better returns on investment therefore stands as an urgent need for research as well as for development policy.

A large literature has now developed on CSA adoption, but the conceptual and theoretical underpinnings of the phenomenon require greater attention (Torquebiau et al., 2018). There is a particular need for a comprehensive typology of on-the-ground CSA practices. A typology enhances conceptual framing of ideas for subsequent empirical analyses (Collier, LaPorte, & Seawright, 2012; Nichter, 2008), and is particularly important for CSA, which includes a diverse array of practices that vary across contexts. Greater conceptual clarity regarding CSA practices is necessary to build knowledge of CSA adoption and ultimate impacts, including by making adoption estimates more comparable across national and sub-national contexts. Such conceptual clarity is also needed to generate more systematic understanding of the potential need for external support to encourage the adoption and retention of particular CSA practices over time.

We respond to this research gap by developing a typology of farm-level CSA practices applicable to households and communities in the developing world. The typology is broadly relevant, with roots in the existing literature on CSA, farmer decision-making, and diffusion of innovation. The categories used in the typology derive from variations in the resource requirements of different farm-level CSA practices. For example, some CSA practices such as the construction and maintenance of soil and water conservation structures like stone bunds and terraces are highly labor intensive while other practices like application of green manure or assisted regeneration are much less resource intensive. Research has shown that CSA adoption and retention rates in different developing world contexts are heterogeneous depending on resource requirements for certain CSA practices (D’Souza & Mishra, 2018; Pedzisa, Rugube, Winter-Nelson, Baylis, & Mazvimavi, 2015; Wakeyo & Gardebroek, 2015). Our typology is designed to help make sense of this heterogeneity and understand which types of practices are more or less likely to be adopted and endure under different circumstances.

This study responds to two major questions on CSA adoption at the farm level in smallholder household and community contexts, particularly in dryland areas. First, what are the most important drivers of the adoption of practices within various farm-level CSA categories? Second, how does an externally supported CSA intervention affect the adoption dynamics of CSA?

We use the typology and the underlying literature to generate hypotheses that we then test using original household survey data from southern Malawi where a large aid-funded program promoted a range of CSA practices. The US$86 million project Wellness and Agriculture for Life Advancement (WALA) was funded by the US Agency for International Development (USAID) through its United in Building and Advancing Life Expectations (UBALE) program and implemented in eight districts in southern Malawi from 2009 to 2014. We estimate CSA adoption as a function of participation in the WALA project as a case study, using recursive bivariate probit (RBP) and propensity score matching (PSM).

By answering the two stated questions, the study advances current scholarship in at least three ways. First, it contributes conceptually to CSA adoption literature by developing and applying a farm-level CSA typology to enhance knowledge of CSA adoption in different smallholder contexts. Second, it identifies CSA categories with higher adoption probabilities under an external CSA intervention. Understanding which CSA categories farmers would most likely adopt under external CSA interventions, which they may otherwise not adopt, is an important first step toward efficient utilization of CSA and climate-related development financing in developing countries. Third, it extends previous adoption literature that rigorously controls for unobserved heterogeneity in program participation in developing country contexts (Abdulai, 2016 in Zambia; Ma, Abdulai, & Goetz, 2017 in China; Tambo & Wünscher, 2017 in

Ghana) by applying RBP to assess the impact of program participation on CSA adoption in southern Malawi.

The rest of this paper proceeds as follows. Section 2.2 describes the typology and its theoretical underpinnings and expectations. It then provides further detail on the case study of CSA promotion in southern Malawi under the WALA project. Section 2.3 presents the conceptual framework, empirical strategy, and data for this study. Section 2.4 presents the results and discussion, while Section 2.5 concludes.

2.2 LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.2.1 The need for a typology of farm-level CSA practices

Typologies are a systematic way of presenting concepts and ideas for constructive decision making (Collier et al., 2012). Typologies are particularly vital aspects of the design and analyses of systems that require comparability, durability, and sustainability because they help in concept formation and refinement as well as in establishing patterns or directionality within systems and structures (Collier et al., 2012; de Groot, Wilson, & Boumans, 2002; Kim, 2014). For instance, typologies can provide a blueprint for systematic and comparable analyses across diverse contexts (Altaweel, Virapongse, Griffith, Alessa, & Kliskey, 2015).

Typologies have aided understanding in diverse social-ecological inquiries including ecosystem services (Altaweel et al. 2015; Bohnke-Henrichs, Baulcomb, Koss, Hussain, & de Groot, 2013; de Groot et al. 2002), community-based natural resource management systems (Altaweel et al., 2015; Ampaire et al., 2017; Khanal, Wilson, Hoang, & Lee, 2017), and food security in the context of climate change (Lopez-Ridaura et al., 2018). To date, however, a farm-level CSA typology is lacking in the literature. Prior studies (Asfaw, McCarthy, Lipper, Arslan, & Cattaneo, 2016; Kpadonou et al., 2017; Sietz & Van Dijk, 2015) analyze CSA adoption based on broad categories such as soil and water conservation and erosion control measures. However, we are not aware of any existing farm-level CSA typology as a tool for empirically analyzing CSA adoption across smallholder households and communities in the developing world.

A potential explanation for the lack of a widely applicable CSA typology is the disparate nature of classifications of CSA across farm, community, and landscape levels (Brandt, Kvakić, Butterbach-Bahl, & Rufino, 2017; Lopez-Ridaura et al., 2018; Mwongera et al., 2017; Notenbaert, Pfeifer, Silvestri, & Herrero, 2017). The typology we develop emphasizes on-the-ground CSA practices that households and communities may implement on their land. This focus can help enhance efficient estimates of smallholder adoption and impacts of CSA by aggregating results across a set of CSA categories that include a variety of specific practices.

Figure 2.1 presents a descriptive, unordered CSA typology consisting of six categories that broadly encompass the range of farm-level CSA practices across smallholder households and communities in the developing world. The typology derives from an extensive review of the literature on CSA and related approaches such as conservation agriculture, sustainable intensification, and sustainable land management, which are widely categorized as subsets of the wider CSA concept (FAO, 2010; 2013; & 2016).

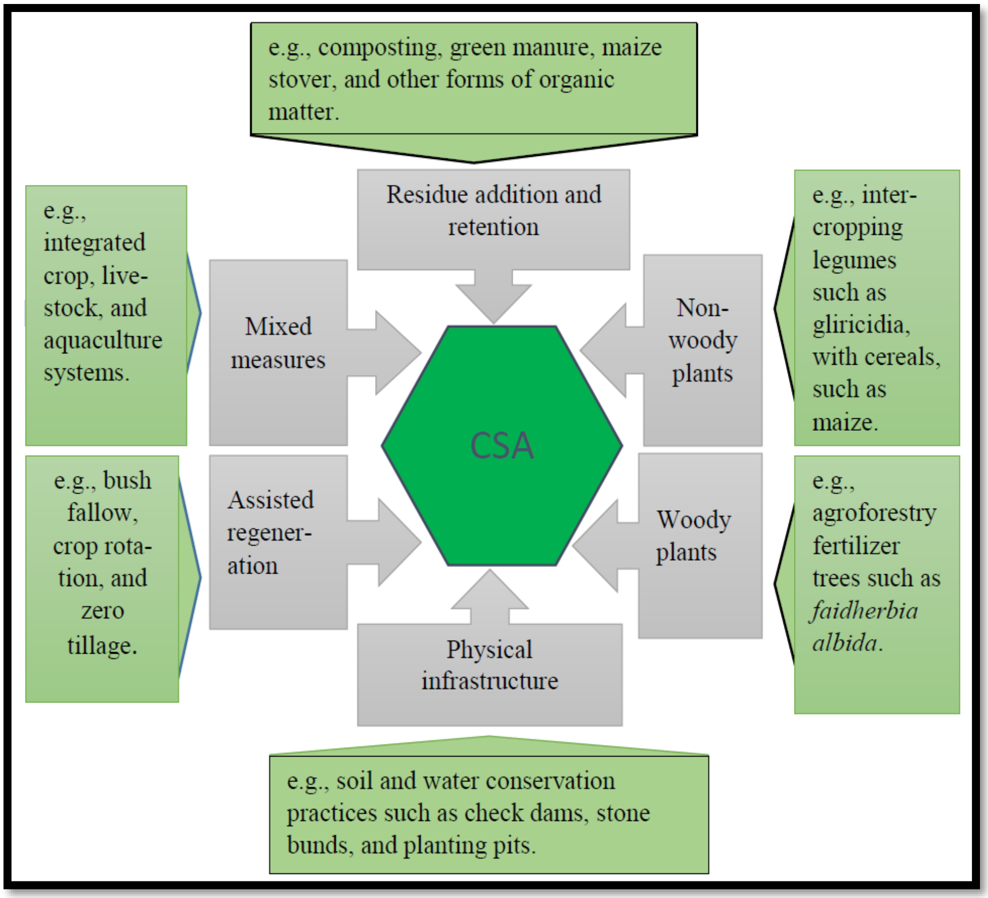

Figure 2.1: A typology of farm-level climate-smart agriculture (CSA) practices.

The categories include:

1) <u>Residue addition and retention</u>: Practices involving the addition, retention, or application of plant residues and animal wastes to the soil to improve organic matter content and soil fertility. Examples include maize straw, organic manure, and composing (Brandt et al., 2017; Gebremariam & Tesfaye, 2018; Kpadonou et al., 2017).

2) <u>Non-woody plants</u>: Practices relating to growing grasses, shrubs, and annual plants or shrubs—usually intercropped with staple crops, but possibly in a crop rotation or in a

monoculture—to enhance soil fertility and diversify income (Djido & Shiferaw, 2018; Ng'ombe, Kalinda, & Tembo, 2017; Thierfelder et al., 2017).

3) Assisted regeneration: Practices relating to soil nutrient restoration after a period of a noticeable reduction in fertility such as crop rotation, bush fallow, and minimum tillage (Dougill et al., 2017; Kpadonou et al., 2017; Thierfelder et al., 2017).
4) Woody plants: Practices relating to growing trees in agroforestry systems, such as fertilizer trees, fruit trees, and indigenous tree species (Garrity et al 2010; Miller, Muñoz-Mora, & Christiaensen et al., 2017).
5) Physical infrastructure: Practices relating to the installation and maintenance of various earthen structures for water harvesting and regulation such as check dams, stone bunds, marker ridges, and irrigation (Gebremariam & Tesfaye, 2018; Hochman et al., 2017; Pradhan & Ranjan, 2016).
6) Mixed measures: The integration of several sets of CSA practices. Examples include crop-livestock diversification systems, system of rice intensification, and organic agriculture, broadly speaking. Combinations of CSA practices as mixed measures could be implemented in an organized or unorganized way to improve soil fertility, sequester carbon, and meet other needs such as improved crop yields (Gebremariam & Tesfaye, 2018; Jaleta, Kassie, Marenya, Yirga, & Erenstein, 2018; Notenbaert et al., 2017).

2.2.2 Theoretical framework and expectations

Theories relating to the diffusion of innovations (Rogers, 1983, 2003), induced innovations (Bishwanger & Ruttan, 1978; Hayami, 1981; Ruttan & Hayami, 1984) provide a means to logically order the categories of CSA practices identified above. These theories are central in the agricultural technology adoption literature and enable categorization of farm-level CSA practices according to adoption and retention probabilities. Together with standard theory on rural household economies in developing countries (de Janvry & Sadoulet, 2006; Singh, Squire, & Strauss, 1986), they also facilitate development of hypotheses about CSA adoption.

Diffusion of innovations theory specifies that the characteristics of an innovation, such as relative advantage, compatibility, complexity, trialability, and visibility will shape the rate of its adoption (Rogers 2003). Importantly, technologies do not necessarily need to be new to meet the definition and dynamics of innovation (Rogers 2003). Induced innovation theory states that resource endowment or constraints, such as labor and capital, will affect the adoption of innovations (de Janvry & Sadoulet, 2006; Jaleta et al., 2018; Pradhan & Ranjan, 2016). Existing research demonstrates that resource availability (including credit access and labor) constitutes a major determinant of the adoption of CSA-related practices like water and other natural management approaches (Chandra, Dargusch, McNamara, Caspe, & Dalabajan, 2017; Lopez-Ridaura et al., 2018; Marenya & Barrett, 2007). Therefore, we expect that highly resource-intensive CSA categories such as physical infrastructure (e.g., check dams, stone bunds, water absorption trenches) will have lower adoption rates absent external support compared to less resource-intensive categories such as adding non-woody plants.

Following Collier et al. (2012), we further refine the typology above into a CSA adoption possibility matrix (Table 2.1) that conceptually links CSA categories with resource demand or requirements. Table 2.1 shows the likely rates of adoption theorized across CSA categories absent external support. The rows and columns respectively represent CSA categories and their characteristics in terms of resource requirements and retention probability. From left to right, CSA categories display resource requirements from low to medium and high in terms of land use, labor, capital, and retention probability after potential adoption. Similarly, from top to bottom, the columns depict likely CSA adoption rates, from the highest rate (easiest to adopt) to lowest rate (most difficult to adopt) absent external support.

Using this organizational logic, the first row of Table 2.1 presents residue addition such as organic matter. This category of CSA practices generally exhibits low resource requirements in terms of land use, labor, and capital, although crop residues may be hard to obtain in some circumstances (Thierfelder et al., 2014; Ward, Bell, Droppelmann, & Benton, 2018). However, compared to practices in the other categories of the typology, smallholder farmers will likely find residue addition to be the easiest CSA category to adopt since natural organic matter is not as hard to obtain in at least moderate amounts compared to the more resource-instensive practices in the other categories.

The second row contains practices relating to non-woody plants such as various grasses and leguminous annuals that are often intercropped or planted along with staple crops like maize to improve the soil (Ouyang et al., 2017; Paustian et al., 2016; Steward et al., 2018). Compared to residue addition, practices in this category may be relatively harder to adopt because they require more land resources. Although easier to adopt, we expect this category and residue addition to have shorter probabilities of retention compared to the subsequent categories.

We expect the category of assisted regeneration, which includes practices that farmers implement to enhance soil fertility as defined earlier, to have a slightly lower adoption probability than residues and non-woody plants absent external support due to higher resource demands. For example, crop rotation, bush fallow, and minimum tillage might require access to larger farm sizes, which are often difficult for small-scale farmers (Dougill et al., 2017; Kpadonou et al., 2017; Thierfelder et al., 2017). However, the potentially higher benefits associated with such practices may mean wealthier farmers or those who receive external support to reduce transaction costs are more likely to adopt and retain them.

Table 2.1: Matrix showing theorized adoption probability for farm-level climate-smart agriculture (CSA) practices based on resource requirements

		Resource requirement							
		Land use		**Labor**		**Capital/cash**		**Retention probability**	
Category of CSA practice	**Examples of specific CSA practices**	Low to medium	High	Low to medium	High	Low to medium	High	Short- to medium-term	Long-term
Residue addition	Green manure	✓		✓		✓		✓	
	Maize stover	✓		✓					
	Animal dung	✓		✓				✓	
Non-woody plants	Various grasses that are either intercropped with staple crops or monocropped (e.g., vetiver grass)*	✓		✓				✓	
Assisted regeneration	Zero or minimum tillage	✓			✓	✓		✓	
	Apiculture to force native tree regrowth*		✓		✓	✓	✓	✓	✓
Woody plants	Agroforestry fertilizer trees (like Faidherbia)*		✓	✓			✓	✓	✓
	Agroforestry fruit trees such as mango*		✓				✓		✓
Physical infrastructure	Stone bunds*		✓		✓		✓		✓
	Check dams*		✓		✓		✓		✓
	Marker ridges*		✓		✓		✓		✓
	Contour trenches*		✓		✓		✓		✓
	Water absorption Trench*		✓		✓		✓		✓
Mixed measures	Integrated crop livestock system		✓		✓		✓		✓
	Aquaculture		✓		✓		✓		✓
	Climate-resistant crop varieties, livestock breeds	✓			✓		✓		✓

*Specific CSA practices and, by extension, CSA categories that were promoted in the Wellness and Agriculture for Life Advancement (WALA) project funded by the US Agency for International Development.

The categories of woody plants (including agroforestry) and physical infrastructure are the most demanding of land use, labor, and capital in our typology. However, they are also potentially the most rewarding (Andrieu et al., 2017; Branca, Lipper, McCarthy, & Jolejole, 2013). Moreover, these two CSA categories are more visible and trialable—favorable characteristics based on the diffusion of innovations theory (Rogers 2003). These characteristics imply that, given the external support that reduces transaction costs of adoption per the theory of induced innovations as explained above (e.g., Ruttan & Hayami, 1984), these two categories would have higher adoption probabilities.

Finally, the last category in our typology contains mixed measures—the simultaneous application of a variety of interrelated practices such as integrated landscape management incorporating livestock with crop production and sheltering them in climate-smart housing (Khatri-Chhetri et al., 2017), and the adoption of climate-resilient crop varieties (Randrianjafizanaka, Autfray, Andrianaivo, Ramonta, & Rodenburg, 2018). Mixed measures are hard to categorize due to the sundry practices they encompass, including some practices captured in the other categories of our typology. Our use of the term "mixed measures" follows general usage in the extant CSA literature (Kpadonou et al., 2017; Sietz & Van Dijk, 2015).

We used the typology together with theories on rural households' decision-making and common-pool resource management in developing countries to develop a set of hypotheses that we then test using data from southern Malawi. For example, well-known theories of rural households (de Janvry & Sadoulet, 2006; Singh et al., 1986) posit that, under market imperfections, farm households' farming and consumption decisions are non-separable. This logic implies a typical farm household in southern Malawi (which most certainly faces market imperfections) makes farming decisions in conjunction with their consumption needs. Following literature on the commons (Agrawal 2001; Cox, Arnold, & Villamayor Tomás, 2010; Ostrom 1991), we also expect that institutional (e.g., extension visits, market access) and biophysical (e.g., elevation, slope, and distance to a main road) factors will also shape farmer decision making regarding CSA adoption. Two hypotheses we develop and test are:

H1: *CSA adoption probability varies by CSA category, household characteristics, biophysical factors, and institutional factors.*

H2. *Participants in an externally funded CSA intervention (e.g., the WALA project) adopt more resource-intensive CSA categories.*

In line with our typology and prior applications of theories of adoption and induced innovation (Dhehibi et al., 2017; D'Souza & Mishra, 2018; Negatu & Parikh, 1999), we expect higher adoption rates for CSA practices in the physical infrastructure and woody plants categories under WALA' s CSA program, compared to those in the assisted regeneration and non-woody plants categories. Project support to reduce transation costs together with the potentially large and lasting benefits of these more resource-intensive practices should lead to higher adoption rates than would be expected in the absence of external funding.

2.2.3 The Wellness and Agriculture for Life Advancement project

To test the hypotheses associated with our farm-level typology, we focus on the USAID-funded CSA intervention WALA implemented in southern Malawi from 2009 to 2014. The goal of WALA was to reduce food insecurity among vulnerable households in the project area by curbing environmental degradation, among other approaches (Soroko, Mapemba, Phillips, & Jordan, 2018; Verduijn, Downen, Walters, & Wyeth, 2014). A consortium of seven non-government organizations (NGOs) led by the Catholic Relief Services (CRS) implemented

WALA. The project had a broad operational reach in southern Malawi covering eight districts (Figure 2.2). It included three major components: (1) maternal and child health nutrition; (2) human and community development activities, such as promoting village savings and loans associations; and (3) community disaster risk reduction through watershed development (i.e., implementation of various CSA-related practices and approaches).

This study focuses on the third component of WALA, which included CSA under a broader set of watershed development activities. This component (henceforth the CSA intervention[4]) comprised training farmers at the community level to protect the natural resource base of their communities and their respective farmlands by implementing CSA practices. The program sought to enhance water retention and reduce erosion, thereby increasing agricultural productivity. To this end, WALA worked with lead farmers and farmer-extension facilitators to mobilize farmers for participation in CSA activities in the project area (see Apendix).

The CSA component of WALA began implementation in 2010 through 2014. WALA promoted CSA through farmer training efforts within grouped village headman (GVH) units.[5] WALA provided "food for assets"[6] to households that participated in developing watersheds at the community level of GVHs. By doing so, individual farmers in the communities can learn about CSA through diffusions of innovations and social learning, thereby adopting these practices on their farms. For this strategy, WALA employed a concept known as the "ridge-to-valley" model, which ensured that community members protected watersheds in the uplands and

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[4] Note that during implementation, WALA did not exclusively use the term *CSA* in its watershed development and disaster risk reduction (DRR) program and climate adaptation across communities. We have operationalized the term *CSA* in this context because the DRR program closely aligns with CSA activities generally, and USAID and implementing partner staff consider this work as being under the CSA umbrella.
[5] GVH is the smallest administrative unit in Malawi, and was the basis of WALA's implementation.
[6] Also known as "food for work (FFW)."

hills around their villages as a public good, and then implemented individual CSA practices on their farms (Soroko et al., 2018; Verduijn et al., 2014).

Thus, WALA provided food for assets, which consisted of 4 liters of vegetable oil and 15kg of pinto beans given to each household that provided labor for the community watershed development work (Verduijn et al., 2014). WALA did not offer any other form of cash transfers for participation in the CSA intervention.

CSA practices under WALA comprised of four out of the six CSA categories in the typology (see Section 2.2.1). They included (1) assisted regeneration (through apiculture by using beehives for improving natural vegetation through afforestation techniques), (2) non-woody plants (mainly dissemination of planting nurseries for vetiver grass), (3) woody plants (including agroforestry fertilizer trees, and fruit trees), and (4) physical infrastructure (such as stone bunds and contour trenches). In line with the hypothesis H2, we expect participation in the CSA intervention under WALA to influence CSA adoption in the direction of the arrow in Figure 2.3. We note that residue addition and mixed measures, though not part of the CSA intervention under WALA, were sometimes practiced in the region and should be accounted for generally to capture the full range of the farm-level CSA categories.

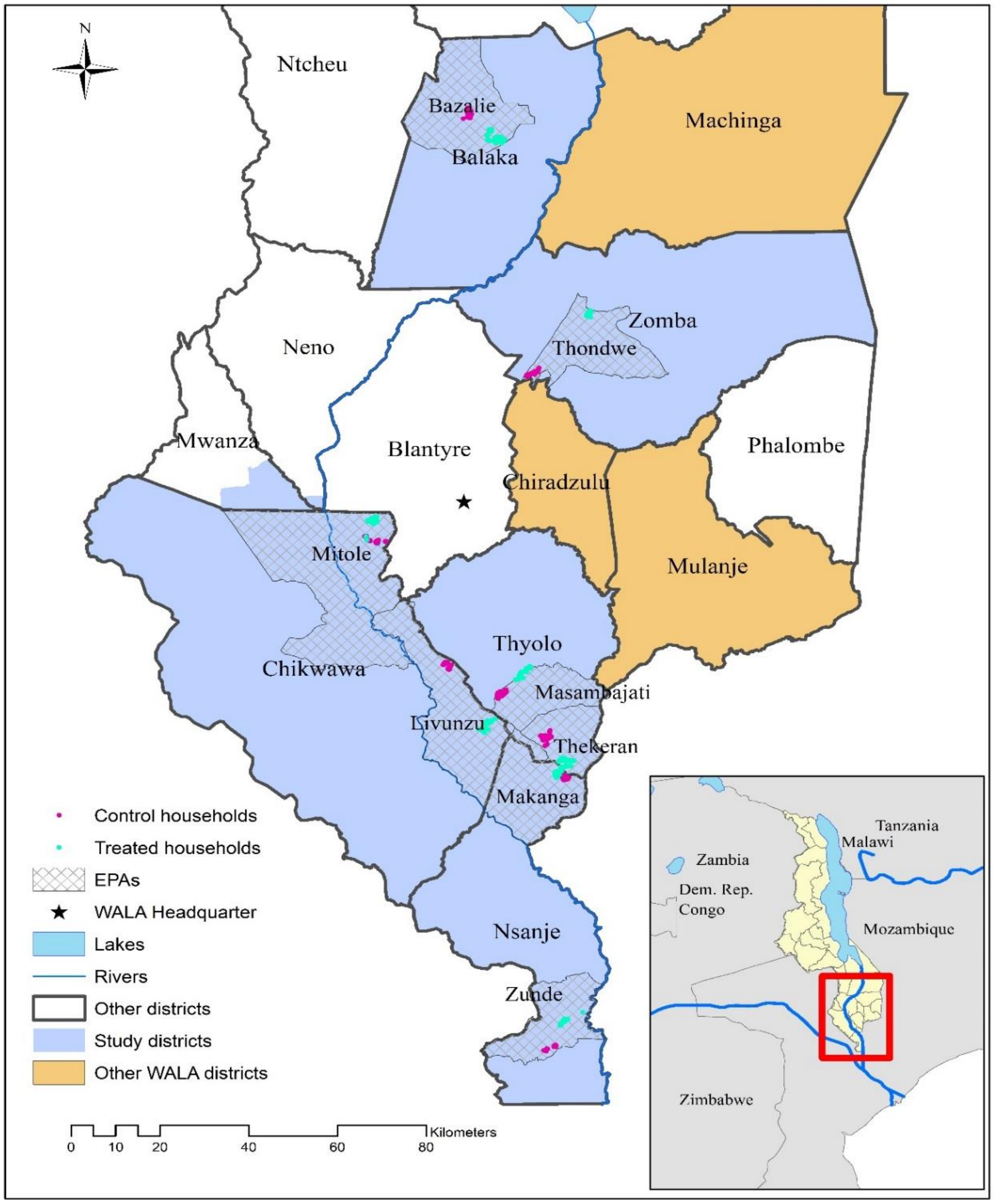

Figure 2.2: Study area showing treated and control households within districts.

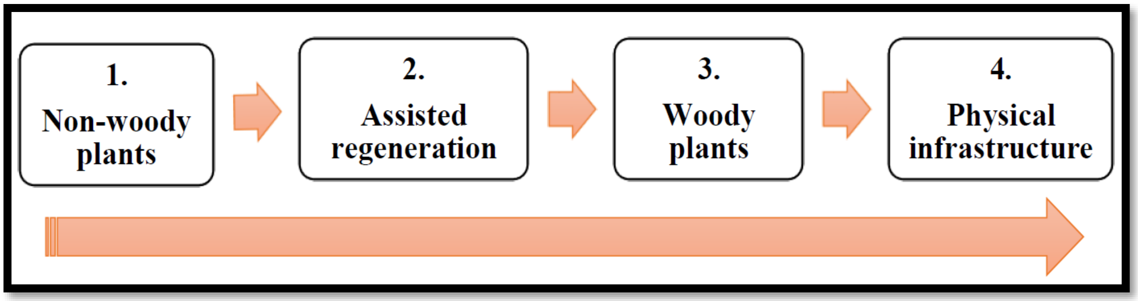

Figure 2.3: Hypothesized direction of climate-smart agriculture adoption categories under the Wellness and Agriculture for Life's Advancement program.

2.3 ECONOMETRIC METHODS AND ESTIMATION TECHNIQUES

2.3.1 Conceptual framework: A quasi-experimental design

We utilize a random utility maximization theory assuming that farm households participate in WALA's climate-smart intervention if the utility of participation (U^P) exceeds the utility of non-participation (U^N). While utility is unobservable, we are able to observe the participation decision (P*), which we express as a binary variable as:

$$P^* = 1 \text{ if } U^P > U^N > 0; \text{ and } P^* = 0 \text{ if } U^N > U^P > 0 \qquad (2.1)$$

Like Lambrecht, Vanlauwe, Merckx, and Maertens (2014), we defined farm households that participated in the CSA intervention under WALA as households resident in a CSA intervention village and having reported receiving training on at least one of the four CSA categories that WALA promoted, and that WALA staff or its affiliates delivered such CSA-related training. Similarly, we define CSA adopters as farmers who were still implementing at least one CSA category on their farms four years after CSA training began (taking 2012 as the reference year). This 4-year timeframe as our measure of CSA adoption corresponds to the time WALA had reached all target communities with its CSA intervention, to 2016 (the time of data collection for this study). We used this period because, although WALA began promoting CSA practices in 2010, full coverage of the entire project area did not occur until 2012 at WALA's midpoint (personal conversations with project management, 2015 and 2016). The four-year period follows similar studies using cut-off periods to define adoption (Coulibaly, Chiputwa, Nakelse, & Kundhlande, 2017; Mutenje, Kankwamba, Mangisonib, & Kassie, 2016; Shiferaw, Kassie, Jaleta, & Yirga, 2014).

We performed several checks to validate project participation. First, we verified the existence of CSA practices on farmers' plots through field visits and double-checked with the farmers regarding when they started implementing CSA practice(s). Second, without mentioning the word "WALA," we asked farmers if they had ever received training from an NGO or group of NGOs in the community during the period coinciding with WALA's operational timeline in their community. If the answer was yes, we probed whether the farmer or a member of his/her household knew the name of the organization, project, or NGO that provided the training, and then asked for specific details of the training they received. Third, we used households' reported number of years of practice of CSA activities to compute various adoption thresholds coinciding with the period of WALA's CSA intervention from 2010 to 2014 (the time CSA support was in effect under WALA). Fourth, we conducted key informant interviews at the community level and obtained farmers' group membership records to verify the participation and adoption claims by individual farmers. Key informants at the farmer group level were able to provide accurate information on the number of households that most likely participated in the intervention in their community.

From equation (2.1), we express the participation decision as a latent variable:

$$P^*_f = \beta X_f + \zeta_i, \text{ for } P = 1, \text{ if } P^*_f > 0, \tag{2.2}$$

where P^*_f represents farm households' participation in CSA intervention. We assume that participation in the CSA intervention[7] exposed subjects to CSA information and technical skills through the training they received. X_f is a vector of exogenous characteristics including household, biophysical, and institutional factors that affect participation and CSA adoption probability. β is a parameter to be estimated, while ζ is a normally distributed error term with zero mean and constant variance. Imposing linearity on the outcome variables (CSA adoption probabilities) along with a dummy variable for the participation variable and other covariates, the outcome equation becomes

$$\Psi^*_f = \theta Z_f + \beta P_f + \xi_f \ , \tag{2.3}$$

where Ψ^*_f is CSA adoption probability, P is participation, θ and β are parameters to be estimated, and ξ is an error term as in equation (2.2).

2.3.2 Empirical specification and identification strategy

We employ two empirical strategies: RBP as the main analytical technique, and propensity score matching as a robustness check for the main estimates.

2.3.2.1 Recursive bivariate probit (RBP)

The RBP model uses a full information maximum likelihood (FIML) algorithm to estimate the selection and outcome equations jointly and accounts for potential endogeneity and selectivity bias in treatment assignment. We estimate four separate RBP models for the four CSA categories in the typology above to determine the effect of program participation on the adoption

[7] We shall also refer to participation in CSA intervention as *treatment* and *selection*, using the terms interchangeably across the paper.

of individual CSA categories conditional on other covariates. From equation (2.3), we specify the following selection and outcome equations jointly:

$$P^*_f = \kappa X_f + \lambda_i, \text{ for } P = 1, \text{ if } P^*_f > 0 \text{ and} \tag{2.4}$$

$$CSA_i{}^*{}_f = \alpha P^*_f + \psi Z_f + \xi_f, \tag{2.5}$$

where P^*_f is a latent variable representing participation, $CSA_i{}^*{}_f$ is the adoption of specific CSA categories, and X_f and Z_f consist of determinants of program participation and specific adoption probabilities, respectively. As stated earlier, these determinants include household characteristics and biophysical and institutional factors (such as extension visits). α, κ, and ψ are parameters to be estimated, while λ_i and ξ_f are stochastic error terms in the system of equations. We assume that the joint error term (Ω) follows a bivariate normal distribution thusly:

$$\Omega = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}, \tag{2.6}$$

where ρ represents the correlation coefficient of the unobserved independent variables in the system of equations (Abdulai, 2016; Amare, Asfaw, & Shiferaw, 2012).

The RBP requires that X_f exclude at least one variable in Z_f, corresponding to program participation and CSA adoption, respectively. That is, a set of valid instrumental variables (IVs) be included in the system. Valid instruments should be highly correlated with the participation decision conditional on other covariates, but uncorrelated with CSA adoption variables. Instrument validity is a major challenge in empirical work such as this study because covariates that affect program participation may also jointly affect CSA adoption (Abdulai, 2016; Djido & Shiferaw, 2018; Ma et al., 2017; Ragasa & Mazunda, 2018).

We identified two potential instruments—distance (in kilometers) from an untreated watershed and perception of the WALA intervention—and perform falsification tests proposed by Di Falco et al. (2011) and applied widely in empirical analyses (e.g., Jaleta et al., 2018; Khonje, Manda, Alene, & Kassie, 2015; Sesmero et al., 2018) to determine their admissibility. If a variable is a valid instrument, it should affect the participation probability, but not the probability of CSA adoption among non-participants. Table 2.2 and Table 2.3 show that these instruments are valid in terms of being jointly statistically significant in the participation equation (Table 2.2,) but not significant in all the adoption equations across CSA categories that WALA promoted, and in accordance with our typology (Table 2.3).

We argue that the results are plausible for the following reasons. First, proximity to an untreated watershed (such as being in a remote WALA intervention community with no previously treated watershed intervention as a proxy for CSA intervention) could influence participation probability in WALA. This is because such communities could be a top priority for contact by WALA staff about their prospect of participation by providing information about the benefits of the intervention. This could affect the participation possibility. However, being in such communities outside WALA's zone of influence (i.e., non-participants in the program) is less likely to affect the adoption of CSA categories that WALA promoted because other factors could affect the decision to adopt CSA other than proximity to an untreated watershed. The longer distances may limit the frequency of interactions with WALA staff, but should not directly influence adoption among non-participants. Second, in terms of the perception of WALA, positive perception of the intervention may influence households' participation. However, we do not expect that it will affect adoption among non-participants of the intervention.

We also assumed that extension visits may be jointly correlated with participation because CSA-program participants are more likely to have received frequent extension visits than non-participants. Therefore, we used a two-stage control function (CF) approach proposed by Wooldridge (2015) to control for the potential endogeneity of extension visits in the participation equation. This approach has been applied empirically in Malawi (Ragasa and Mazunda 2018) as well as several other developing countries, including China (Ma et al., 2017) and South Africa (Tesfamariam, Owusu-Sekyere, Donkor, & Tlalang, 2018).

Table 2.2: Instrument validity test for the selection equation

Selection equation/Participation				
Instrument	Coefficient	Std. Error	Z-statistics	P-value
Distance to untreated watershed	0.047***	0.008	6.020	0.000
Perception of WALA	2.327***	0.120	19.470	0.000
Constant	-1.252***	0.094	-13.360	0.000
Model diagnostics				
Log likelihood	-281.554			
LR chi2	545.35***			0.000
Pseudo R2	0.492			
Observations	807.000			

Significance level: *** < 1%
Note: WALA, Wellness and Agriculture for Life Advancement; LR, Likelihood Ration ch2, Chi-squared; Pseudo R2, Pseudo R-squared tests.

Using the CF approach, we regressed the extension variable as a function of all explanatory variables of the participation equation plus an IV. We used distance to the district headquarters as an IV for the extension variable because it affects the frequency of extension visits but not necessarily the probability of participation in the program as other factors, such as farmers' memberships and gender of the household head, could be more important for participation based on WALA's selection criteria. In the second stage, we include the predicted residuals from the first stage extension model in the participation equation as an additional control, as done in related work by Ma et al. (2017), Ragasa and Mazunda (2018), and Tesfamariam et al. (2018). The CF therefore proceeded accordingly;

$$Ev_i = \eta Ki + \pi X_i + \omega_i, \tag{2.7}$$

where Ev_i represents extension visits, Ki represents an instrument for the extension variable in the adoption equation, and X_i represents observed characteristics. Following equations (2.5) and (2.7), the form of our adoption equations becomes

$$\Psi_{fi} = \alpha Z_{fi} + \beta P_{fi} + E_{res} + \xi_{fi}\,, \tag{2.8}$$

where Ψ^*_f is CSA adoption, P_{fi} is households participation probability in WALA's watershed program, Z_f consists of determinants of participation in WALA's CSA as defined above. E_{res} is the extension residual generated from equation (7), while α, β, and ξ are parameters to be estimated.

Following Abdulai. (2016) and Ma et al. (2017), we compute the average treatment effect on the treated (ATT), i.e., the actual effect of program participation on CSA adoption, as follows:

$$ATT = E\{[(CSA_i = 1)|P_f = 1] - [(CSA_i = 0)|P_f = 1]\}\,, \tag{2.9}$$

where $E[(CSA_i = 1)|P_f = 1]$ is the expected probability of CSA adoption among program participants, and $E[(CSA_i = 0)|P_f = 1]$ is the expected probability of adoption among non-participants.

Table 2.3: Instrument validity check for climate-smart agriculture (CSA) adoption categories under Wellness and Agriculture for Life Advancement (WALA) program

CSA categories under WALA				
Instrument	Coefficient	Std. Error	Z-statistics	P-value
Non-woody plants				
Distance to untreated watershed	-0.016	0.018	-0.890	0.373
Perception of WALA	-0.672	0.436	-1.540	0.123
Constant	-1.224***	0.113	-10.810	0.000
Model diagnostics				
Log likelihood	-108.180			
LR chi2	3.84			0.1463
Pseudo R2	0.0175			
Observations	358			
Assisted regeneration				
Distance to untreated watershed	-0.012	0.013	-0.890	0.374
Perception of WALA	0.329	0.230	1.430	0.153
Constant	-0.854***	0.095	-9.000	0.000
Model diagnostics				
Log likelihood	-175.382			
LR chi2	3.04			0.2184
Pseudo R2	0.0086			
Observations	358			
Woody plants				
Distance to untreated watershed	0.006	0.011	0.560	0.577
Perception of WALA	-0.059	0.259	-0.230	0.822
Constant	-0.961***	0.095	-10.100	0.000
Model diagnostics				
Log likelihood	-164.815			
LR chi2	0.37			0.8297
Pseudo R2	0.0011			
Observations	358			
Physical infrastructure				
Distance to untreated watershed	-0.004	0.010	-0.410	0.684
Perception of WALA	0.053	0.219	0.240	0.807
Constant	-0.310***	0.083	-3.740	0.000
Model diagnostics				
Log likelihood	-236.59			
LR chi2	0.24			0.8853
Pseudo R2	0.0005			
Observations	358			

Significance level: *** < 1%

Note: LR, Likelihood Ration ch2, Chi-squared; Pseudo R2, Pseudo R-squared tests.

2.3.2.2 Propensity score matching

Next, we utilized propensity score matching (PSM) as a robustness check for the RBP estimates of treatment effects in terms of the ATT. PSM creates an artificial control group to estimate a program's counterfactual (Rosenbaum & Rubin, 1985). The propensity score is the conditional probability of assigning observational units to a treatment group, given a number of characteristics. It is the participation probability, expressed as

$$p(Z_i) = pr\ (\theta_i = 1/Z_i)\ , \tag{2.10}$$

where $p(Z_i)$ is the propensity score, θ_i is the treatment assignment, and Z_{is} are observable characteristics. Although PSM does not control for unobserved heterogeneity in treatment assignment, it is an increasingly useful tool in empirical studies as a robustness check for other estimation methods that account for unobserved heterogeneity. Examples of recent similar studies that have applied PSM as a robustness check include Khonje et al. (2015), Pradhan and Ranjan (2016), and Ragasa and Mazunda (2018).

We compute the ATT as

$$\begin{aligned} \text{ATT} &= E\{\Psi_{1i} - \Psi_{0i} | V_i = 1\} = E[E\{\Psi_{1i} - \Psi_{0i} | V_i = 1, \text{p(Zi)}\}] \\ &= \{E\{\Psi_{1i} | V_i = 1, \text{p(Zi)}\} - E\{\Psi_{0i} | V_i = 0, \text{p(Zi)}, \text{p(Zi)}\} | V_i = 1\}\ , \end{aligned} \tag{2.11}$$

where Ψ_1 and Ψ_0 are CSA adoption participants and non-participants in watershed development (WALA's CSA intervention), respectively. All other parameters are as defined earlier. We used a nearest neighbor matching (NNM) algorithm for the PSM across all models.

2.3.3 Data

Data come from a survey of 808 households sampled from the WALA project's watershed intervention area in southern Malawi (see Figure 2.2). We use household- and plot-level data in all specifications for this analysis. Fieldwork occurred from November 2015 to September 2016 in two stages. A scoping trip was first made in November–December 2015 that then informed the main data collection effort, which was carried out from July to September 2016. We sampled households from five districts in the WALA intervention communities where CSA implementation occurred (see Figure 2.2).

To select households for inclusion in the survey we used a multistage proportional sampling method in communities where WALA focused its CSA promotion efforts as well as in control communities located outside the WALA intervention area. We selected a sample of two extension planning areas (EPAs) per district based on the location of treated and control GVHs. EPAs are the largest local administrative units in which WALA's CSA intervention occurred. Each selected EPA contained a set of treated and non-treated villages wherein we also employed proportional sampling based on the size of the GVHs to select households within them. Our approach followed procedures used in similar empirical studies (Djido and Shiferaw 2018; Herrmann 2017; Pradhan and Ranjan 2016). Our sample contained 450 households from treatment communities and 358 control households (Table 2.4). Most EPAs have more households from the treatment villages than control villages, except for Thekeran EPA, which had the opposite—74 in control villages and 63 in treatment villages. This is due to the proportional sampling across communities in the study area as explained above.

Table 2.4: Distribution of sampled households by treatment and control status

District	Extension planning area	Watershed treatment status by household		Total households per EPA
		Treated (1)	Control (0)	
Balaka	Bazalie	61	29	90
Chikwawa	Livunzu	60	58	118
Chikwawa	Mitole	72	37	109
Nsanje	Makhanga	45	34	79
Nsanje	Zunde	41	41	82
Thyolo	Masambajati	65	51	116
Thyolo	Thekeran	63	74	137
Zomba	Thondwe	43	34	77
N = 5	Total = 8	450	358	808

Source: Authors' calculation using WALA's ex-post survey data, 2016

We used a questionnaire designed for this study and administered by Malawian enumerators fluent in the main local languages. The lead author closely supervised the fieldwork to ensure data quality. All enumerators received intensive training for three consecutive days, plus an extra day for pretesting the questionnaire in Mulanje, a WALA district, which was not part of this study.

2.3.4 Main variables and theoretical expectations

Table 2.5 shows the main variables in this study, and their a priori expectations on the outcomes, including participation in the CSA program under WALA, and CSA adoption probabilities. From the literature, we expect many of the covariates to positively influence participation and CSA adoption.

Table 2.5: Definitions of main variables and a priori expectations

Variable	Description	A priori expectations for CSA adoption	Indicative reference
Selection			
Participation (1/0)	Dummy variable = 1 if household participated in CSA program under WALA, otherwise 0	+	Ma et al. (2017); Tesfamariam et al. (2018)
Outcome			
Non-woody plants	Adoption of non-woody plants such as vetiver grass	+	Ma et al. (2017)
Assisted natural regeneration	Participation in apiculture for the adoption of CSA	+	Ma et al. (2017)
Woody plants	Adoption of woody plants such as fertilizer trees	+	Miller et al. (2017)
Physical infrastructure	Adoption of physical infrastructures such as stone bunds and water absorption trench	+	Abdulai and Huffman (2014)
Household-level factors			
Age	Reported age of the household head (years)	+	Coulibaly et al. (2017)
Education	Number of years the household head spent in school (years)	+	Coulibaly et al. (2017)
Female-headed household (1 = yes)	Dummy for whether the household head is a female	Ambiguous	
Household size	The reported number of people per household	Ambiguous but expected to be + here.	Abdulai and Huffman (2014)
Group membership	Dummy = 1 if the household head belonged to a farmers' group before WALA	+ indicates social capital	
Kinship network	Close relatives the household counts on for support in and outside the village	Ambiguous	Di Falco and Bulte (2013)
Off-farm income	Dummy for whether the household has non-farm livelihood sources (1 = yes, 0 otherwise)	Ambiguous; depends on outcome.	Woldeyohanes et al. (2017)
Land ownership (1/0)	Dummy for whether the household head owns land (1 = yes; 0 otherwise)	+ indicates financial capital	Herrmann (2017)

Table 2.5 cont'd

Variable	Description	A priori expectations for CSA adoption	Indicative reference
Number of plots	Total number of plots cultivated by the household in the past two years	+	
Maize plots size	Size (acres) of the household's main plots with maize	+	Abdulai and Huffman (2014)
Hired labor	Dummy for hired labor	Positive effect	Abdulai (2016)
Fertilizer use	Dummy = 1 for fertilizer use in past 2 years	+	Abdulai (2016)
Fertilizer cost	Cost of fertilizer applied	+	Abdulai (2016)
Food aid	Dummy for whether the household received any food aid in the past 1 year	Ambiguous depending on the outcome	Coulibaly et al. (2017)
Livestock ownership (1/0)	Dummy for whether the household has livestock (1 = yes, 0 otherwise)	Ambiguous depending on the outcome types	Woldeyohanes et al. (2017)
Institutional factors			
Extension visit	Approximate number of contacts with extension agents in 2016	+, since it measures information	Ma et al. (2017); Abdulai (2016)
CSA-related technology	Dummy for whether the household had implemented any CSA-related practice outside of WALA (1 = yes, 0 otherwise)	+ indicates information acquisition.	Kpadonou et al. (2017) Kassie et al. (2015)
Credit constraint	Dummy = 1 if the household felt credit constrained in 2015/2016 cropping season	-ve	Abdulai (2016)
Food aid	Dummy = 1 if the household received drought-related food aid in 2015/16.	-ve, as it indicates climate shock	
Biophysical factors			
House elevation	House elevation in meters	Ambiguous	-
Plot is steep	Dummy = 1 if the maize plot is steep	+	
Perception of soil fertility	Dummy = 1 if the household considers the maize plot as fertile or not.	+	
Distance to a treated watershed	Distance in KM to treated watershed in the community or neighboring area.	-ve	

Table 2.5 cont'd

Variable	Description	A priori expectations for CSA adoption	Indicative reference
District			
Balaka	Dummy for whether the household resides in Balaka District (1 = yes, 0 otherwise)	Ambiguous	Coulibaly et al. (2015)
Chikwawa	Dummy for household residing in Chikwawa District (yes = 1, 0 otherwise)	Ambiguous.	Coulibaly et al. (2015)
Nsanje	Dummy for whether the household resides in Nsanje District (1 = yes, 0 otherwise)	Ambiguous.	Coulibaly et al. (2015)
Thyolo	Dummy for whether the household resides in Thyolo District (1 = yes, 0 otherwise)	Ambiguous.	Coulibaly et al. (2015)
Zomba	Dummy for whether the household resides in Zomba District (1 = yes, 0 otherwise)	Ambiguous.	Coulibaly et al. (2015)
Instrument			
Distance to district headquarters	Distance from the plot to the district headquarters town (km).	-ve for participation, neutral for adoption	
Distance to an untreated watershed	Distance in km to an untreated watershed in the community or neighboring area	-ve for participation, neutral for adoption	
Perception of WALA	Dummy = 1 if household has positive perception of the WALA program	+ for participation, neutral for adoption	

Note: CSA, climate-smart agriculture; WALA, Wellness and Agriculture for Life's Advancement

2.3.5 Descriptive and summary statistics

2.3.5.1 Dependent variables

Table 2.6 shows summary statistics of the dependent variables by specific CSA category that WALA promoted. This table also reports on statistical differences between treatment and control households using a t-test. WALA treatment households have higher adoption rates for all CSA categories, as expected. For instance, the average adoption differences are 33% for non-woody plants, 31% for assisted regeneration, 43% for woody plants, and 57% for physical infrastructure.

Table 2.6: Summary statistics for main climate-smart agriculture (CSA) categories as dependent variables

Variables	Treatment households (N = 450)				Control households (N = 358)				Difference (N = 808)
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	
Adoption by CSA category									
Non-woody plants	0.422	0.290	0	1	0.092	0.494	0	1	0.330***
Assisted regeneration	0.504	0.397	0	1	0.196	0.501	0	1	0.309***
Woody plants	0.602	0.379	0	1	0.173	0.491	0	1	0.429***
Physical infrastructure	0.940	0.485	0	1	0.374	0.238	0	1	0.566***

Significance level: *** < 1%
Note: SD, standard deviation; differences based on t-test, computed using Stata 15MP.

2.3.5.2 Main explanatory variables (covariates)

Table 2.7 shows descriptive statistics of the main covariates used in our analysis and their differences across treatment and control groups. There are some similarities across the two groups in terms of some household characteristics (e.g., age, household size, and education level of the household head), some resource endowment factors (e.g., off-farm income, average plot size, and average number of plots). Moreover, there is broad similarity between treatment and control households in terms of their geographic distributions within the districts. The exceptions are Balaka and Thyolo. The reasons for differential numbers of treated and control households in these two districts is likely due to differential community size resulting from the proportional sampling technique the study used.

There are also a number of statistically significant differences between treatment and control groups. These include household characteristics (such as gender of household heads), resource endowment (such as group membership, kinship networks, and land ownership), institutional factors (including extension visits), and biophysical factors (including house and plot elevation). For instance, treatment households generally had more land and social capital than control households did. On average, 68.7% of treatment households owned land compared to 42.2% of control households. Similarly, on average, 85.6% of treatment households are farmers' group members compared to an average of 37.4% for control households. Treatment households also reported much higher rates of hired labor (76.9%) compared to control households (10.1%).

Some other key differences include number of extension visits, with program participants reporting 9.1 extension visits on average during the 2016 cropping season compared to 5.1 on average for non-participants, and much greater application of fertilizer among treatment households (81.6% on average) than among control households (24.6%) of non-participants. There were also statistically significant differences in credit access, receipt of food aid, and several biophysical factors.

The differences between the two groups are important to note as they may have shaped the selection process into the WALA CSA program. They also imply that analytical methods that do not account for such differences could produce biased estimates of the treatment effect because participants and non-participants could be systematically different. As described above, our approach explicitly seeks to addresses such potential bias by controlling for unobserved heterogeneity between participants and non-participants in the CSA program under WALA, which could influence the adoption of CSA across the project area.

Table 2.7: Summary statistics for main covariates

	Treatment (N = 450)				**Control (N = 358)**				**Difference**
Variable	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**(N = 808)**
Household characteristics									
Age of household head	43.607	15.877	18	89	41.852	15.265	18	87	1.755
Female-headed household	0.416	0.499	0	1	0.536	0.493	0	1	-0.121***
Years of education	4.647	1.965	0	13	4.559	1.867	0	12	0.088
Household size	6.318	2.287	2	12	6.57	2.337	1	12	-0.252
Resource endowment									
Farmers' group member (1 = yes)	0.856	0.485	0	1	0.374	0.352	0	1	0.481***
Kinship network	3.78	1.246	0	6	0.849	1.733	0	6	2.931***
Off-farm income (1 = yes)	0.211	0.386	0	1	0.182	0.409	0	1	0.03
Land ownership (1 = yes)	0.687	0.495	0	1	0.422	0.464	0	1	0.265***
Total number of plots	1.833	0.873	1	5	1.885	0.848	1	5	-0.052
Maize plot size	1.708	0.746	0	4	1.655	0.794	0.4	5.25	0.053
Hired labor	0.769	0.301	0	1	0.101	0.422	0	1	0.668***
Fertilizer use	0.816	0.388	0	1	0.246	0.431	0	1	0.570***
Fertilizer cost	10.083	7.751	0	58	8.346	6.859	0	51	1.737***
Livestock ownership (1 = yes)	0.499	0.495	0	1	0.427	0.501	0	1	0.072**
Institutions									
Extension visits	9.051	2.313	1	12	5.061	2.623	2	17	3.990***
CSA-related technology	0.816	0.431	0	1	0.246	0.388	0	1	0.570***
Credit constrained (1 = yes)	0.364	0.501	0	1	0.492	0.482	0	1	-0.127***
Food aid (1 = yes)	0.653	0.475	0	1	0.341	0.476	0	1	0.313***
Biophysical									
House elevation	444.407	332.493	46	1069	509.05	334.378	24	1284	-64.64***
Plot is steep (1 = yes)	0.533	0.496	0	1	0.433	0.499	0	1	0.100***
Perception of soil fertility	0.882	0.485	0	1	0.377	0.323	0	1	0.505***
Distance to treated watershed	2.69	11.121	1	78	15.532	3.428	0	25	-12.84***
District									
Balaka	0.136	0.273	0	1	0.081	0.343	0	1	0.055**
Chikwawa	0.293	0.442	0	1	0.265	0.456	0	1	0.028
Nsanje	0.191	0.408	0	1	0.209	0.394	0	1	-0.018

Table 2.7 cont'd

Variable	Treatment (N = 450) Mean	SD	Min	Max	Control (N = 358) Mean	SD	Min	Max	Difference (N = 808)
Thyolo	0.284	0.477	0	1	0.349	0.452	0	1	-0.065**
Zomba	0.096	0.294	0	1	0.095	0.294	0	1	0.001
Instrument variables									
Distance to an untreated watershed	8.539	6.837	0	60	3.973	9.413	0	70	4.566***
Perception of WALA	0.857	0.308	0	1	0.106	0.350	0	1	0.751***
Distance to district headquarters	17.413	10.607	0.4	40	17.299	14.141	0.8	81.2	0.113

Significance levels: *** < 1%; ** < 5%

Note: CSA, climate-smart agriculture; WALA, Wellness and Agriculture for Life's Advancement; differences based on t-tests, computed using Stata 15MP

2.4 RESULTS AND DISCUSSION

This section presents analytical results of our estimation of CSA adoption under the WALA program, using RBP as the main analytical technique, and PSM as a robustness check. We estimated four sets of RBP equations for the four CSA categories promoted by WALA (including non-woody plants, assisted regeneration, woody plants, and physical infrastructure). The results are in line with the hypotheses developed from the typology above.

H1 suggested that: CSA adoption probability varies by CSA category and household characteristics, biophysical factors, and institutional factors.

Moreover, we have a particular interest in testing *H2*, given our focus on an externally funded CSA project.

H2 suggested that: *Participants in an externally funded CSA intervention (e.g., the WALA project) adopt more resource-intensive CSA categories.*

Sections 2.4.1 and 2.4.2 discuss these results respectively.

2.4.1 Determinants and extent of CSA adoption across CSA categories under WALA

Table 2.8 shows the marginal effects of program participation and other covariates on the adoption of CSA that WALA promoted. Similarly, Table 2.9 shows the RBP estimates of the average treatment effects on the treated for program participation on adoption of the specific CSA categories from our typology.

For each CSA category, we simultaneously estimated a program participation[8] and the corresponding adoption (outcome) equations using FIML (see Section 2.3.2). These simultaneous equations highlight the effects of program participation and various covariates on CSA adoption across categories. Ideally, in a normal probit model, estimated coefficients are interpretable in such a way that variables with the same names have similar interpretations across models. For example, the effect of the age of household head on the adoption of non-woody plants could be interpreted in the same way for all other CSA categories in this study.

However, the estimated coefficients of the covariates in the RBP model cannot be directly interpreted in terms of the effects of covariates on the outcome (Abdulai, 2016; Ma et al., 2017; Thuo et al., 2014). Therefore, we compute the marginal effects of all covariates to explain their effects on CSA adoption across the typology in terms of CSA categories promoted by WALA. Moreover, it is standard to interpret the estimated marginal effects of the RBP model as elasticities.

Table 2.8 shows a positive and statistically significant marginal effect of participation in the WALA CSA intervention, on all CSA categories in our typology that WALA promoted,

[8] Because the focus here is primarily on the impact of program participation on CSA adoption, we do not report the selection equations across the respective models, even though each model has a selection and outcome component.

except for non-woody plants, for which the marginal effect of participation is not statistically significant. Table 2.8 suggests that on average, participation in the CSA program under WALA increased the adoption probabilities of assisted regeneration practices, woody plants, and physical infrastructure by 36%, 41%, and 49%, respectively. The incremental differences in magnitude for these marginal effects suggest that our data confirm the underlying hypotheses in our typology as discussed above.

Table 2.8 also shows statistically significant marginal effects of some covariates on CSA adoption. For example, kinship networks have a statistically significant marginal effect of 2% on non-woody plants, but not statistically significant on the adoption of any of the other CSA categories. This suggests the ambiguous nature of kinships in terms of technology adoption (see for example, Di Falco & Bulte, 2013 which provides a review and analyses of kinship networks on the adoption of climate risk mitigation practices and finds ambiguous effects of kinships). Off-farm income has positive marginal effects on assisted regeneration and woody plants, but statistically significant for woody plants only. On the other hand, it has negative but statistically insignificant effects on non-woody plants and physical infrastructure. Plot size has a positive and statistically significant marginal effect on the adoption of physical infrastructure at 4%, suggesting the relatively resource-intensive nature of this CSA category compared to others in the typology.

Livestock ownership has a negative and statistically significant effect on the adoption of physical infrastructure at 7%, also suggesting that livestock ownership diverts resources (such as time and capital) away from the adoption of CSA practices in the physical infrastructure category. This result supports our theoretical expectation. House elevation has a negative and statistically significant marginal effect on the adoption of assisted regeneration practices.

Farmers' perceptions of soil fertility suggest that they would adopt physical infrastructure to conserve the fertility of their land. Conversely, distance to a treated watershed has a positive and statistically significant effect on adoption of physical infrastructure. This suggests that farmers who have plots farther from treated watersheds may tend to adopt physical infrastructure practices to potentially prevent degradation of their plots. On the other hand, those with plots closer to a treated watershed may tend to reduce the adoption of physical infrastructure practices, potentially because watershed development is a public good and they can benefit from others' efforts. This is implication of free riding.

Moreover, Table 2.8 shows that adoption of woody plants and physical infrastructure have statistically significant marginal effects on the adoption of non-woody plants by 10.4% and 13.6% respectively. Similarly, adoption of non-woody plants has positive and statistically significant marginal effects on the adoptions of woody plants and physical infrastructure practices, with a marginal effect of 13.7% and 9.4% respectively. This result also supports our theoretical expectations above. For instance, some studies (e.g., Kpadonou et al., 2017; Sietz & Van Dijk, 2015; Sommer et al., 2018) have found complementarr relationships among CSA practices as in this study.

In terms of district dummies, Table 2.8 shows that farmers in Chikwawa are more likely to adopt non-woody plants than those in Nsanje and Thyolo. They are also more likely to adopt assisted regeneration practices than farmers in Balaka but are less likely than farmers in Zomba. Similarly, being in Zomba increases the marginal effect of adopting woody plants by 13.7% compared to a resident in Chikwawa. Additionally, farmers in Chikwawa are more likely to adopt physical infrastructure than those in Balaka and Thyolo.

The results in Table 2.8 strongly support **H1** above. Further research may however, be needed to explain these heterogeneities in CSA adoption across districts in the study area, and to also show the effects of individual impacts of CSA categories on various outcomes such as food security and environmental conservation.

Table 2.8: Recursive bivariate probit estimates of the marginal effects of program participation and covariates, on the adoption of climate-smart agriculture categories

Variable	Non-woody plants		Assisted regeneration		Woody plants		Physical infrastructure	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Participation	0.109	0.084	0.356***	0.100	0.413***	0.105	0.491***	0.069
Age	0.001	0.001	-0.001	0.001	0.002*	0.001	-0.001	0.001
Female household-head	-0.046	0.028	-0.006	0.032	-0.037	0.031	0.043	0.023
Education level (years)	-0.002	0.007	0.004	0.008	0.008	0.008	-0.009	0.006
Household size	0.000	0.006	-0.006	0.007	0.000	0.007	0.007	0.005
Group membership	-0.031	0.038	0.024	0.043	0.016	0.042	-0.020	0.031
Kinship network	0.020*	0.010	0.007	0.013	-0.009	0.012	0.000	0.009
Off-farm income	-0.005	0.035	0.034	0.041	0.095*	0.039	-0.043	0.032
Land ownership	0.023	0.029	0.019	0.034	0.037	0.033	-0.021	0.024
Total number of plots	-0.006	0.016	0.007	0.018	-0.013	0.018	0.023	0.013
Maize plot size	-0.013	0.018	-0.028	0.021	-0.004	0.021	0.041*	0.017
Hired labor	-0.034	0.037	-0.108*	0.044	0.005	0.044	-0.042	0.044
Livestock ownership	0.048	0.028	-0.016	0.033	-0.051	0.031	-0.076**	0.026
Extension visits	0.003	0.006	0.001	0.007	-0.019**	0.006	-0.001	0.005
Fertilizer use	0.028	0.035	0.039	0.043	-0.047	0.043	-0.006	0.032
Fertilizer cost	-0.002	0.002	-0.002	0.002	0.001	0.002	-0.001	0.002
Credit constraint	-0.126*	0.056	0.042	0.072	-0.053	0.068	-0.011	0.061
Food aid	0.016	0.031	-0.090*	0.036	-0.039	0.035	0.020	0.028
House elevation	-0.000	0.000	-2.6E-04**	0.000	7.3E-4	0.000	8.E-05	0.000
Plot is steep	-0.121*	0.053	0.067	0.069	-0.053	0.065	0.027	0.058
Soil fertility	-0.001	0.038	-0.042	0.043	-0.044	0.041	0.064*	0.028
Distance to a treated watershed	-0.001	0.002	0.000	0.002	-0.002	0.003	0.004**	0.001

Significance levels: * < 10%; ** < 5%; *** < 1%; SE, Standard error

Source: Authors' calculation using Stata 15MP

Table 2.8 cont'd

Variable	**Non-woody plants**		**Assisted regeneration**		**Woody plants**		**Physical infrastructure**	
	Coefficient	**S.E**	**Coefficient**	**S.E**	**Coefficient**	**S. E**	**Coefficient**	**S.E**
District								
Balaka	-0.106	0.062	-0.264**	0.086	0.047	0.073	-0.225***	0.067
Nsanje	-0.213***	0.042	0.005	0.048	0.037	0.047	-0.064	0.039
Thyolo	-0.265***	0.047	0.078	0.057	0.055	0.056	-0.120*	0.050
Zomba	-0.028	0.085	0.284**	0.094	0.168	0.095	-0.065	0.076
CSA practice								
Non-woody plants			-0.026	0.039	0.137***	0.035	0.094*	0.036
Assisted regeneration	-0.015	0.030			0.009	0.033	-0.020	0.027
Woody plants	0.104***	0.028	0.016	0.035			0.049	0.027
Physical infrastructure	0.136**	0.044	-0.030	0.046	0.074	0.043		

Significance levels: * < 10%; ** < 5%; *** < 1%; Chikwawa is the base category district

Source: Authors' calculation using Stata 15MP

2.4.2 Average treatment effects of CSA program participation on the adoption of CSA categories in typology in line with WALA.

From a policy perspective, it is useful to estimate the actual impacts of program participation on those who actually participated. That is, the ATT of the program, apart from the average marginal effect from a random household in the population. Thus, the program's ATT is important because it provides a reasonable estimate of the program's counterfactual for the various adoption outcomes. Table 2.9 presents these estimates of ATTs based on RBP and PSM. PSM provides an additional robustness check for our parametric estimates using RBP. The results show that participation in the CSA intervention significantly enhances the probability of CSA adoption across all specifications because the ATTs are statistically significantly different from zero for each.

Table 2.9 shows that the RBP estimates of the ATTs are 41% for non-woody plants, 49% for assisted regeneration, 61% for woody plants, and 94% for physical infrastructure. PSM estimates are similar: 39.8% for non-woody plants, 43.6% for assisted regeneration, 55.5% for woody plants, and 78.4% for physical infrastructure.

The slightly smaller PSM estimates of the ATTs relative to the RBP suggest the effects of unobserved heterogeneity in the sample, which PSM does not account for (Khonje et al., 2015; Tesfamariam et al., 2018). Generally, though, these results provide strong evidence that the CSA work under the WALA project in southern Malawi was effective in influencing CSA adoption in general, but more for resource-intensive categories that farmers would otherwise not adopt.

The result in Table 2.9, therefore, supports our hypothesis H2 that externally funded CSA intervention enhances the adoption of resource-intensive CSA categories that would otherwise not be adopted.

Table 2.9: Treatment effects of participation in Wellness and Agriculture for Life's Advancement (WALA) program on the adoption of climate-smart agriculture (CSA) by CSA category

Outcome variable	RBP			PSM		
	ATT	**Std. errors**	**Z-stats**	**ATT**	**SE**	**T-stats**
Binary adoption probability of CSA practice categories promoted by WALA						
Non-woody plants	0.4120***	0.0242	17.020	0.3987***	0.1453	2.740
Assisted regeneration	0.4970***	0.0248	20.040	0.4365***	0.1599	2.730
Woody plants	0.6123***	0.0252	24.330	0.5546***	0.1279	4.340
Physical infrastructure	0.9411***	0.0108	87.440	0.7840***	0.2305	3.400

Significance levels: *10%; **5%; ***1%

Note: RBP, recursive bivariate probit; ATT, average treatment effects on the treated; PSM, propensity score matching

Source: Authors' calculation using Stata 15MP

2.5. CONCLUSION

CSA is increasingly important for sustainable rural development in developing countries in the face of climate change and extreme weather fluctuations. It is especially useful for rural communities of drier regions such as Sub-Saharan Africa prone to high vulnerability to climate change impacts. However, the reported CSA adoption rate remains low in many contexts despite widespread efforts to increase it across the developing world. Lack of conceptual clarity of how to sort the universe of CSA practices for better adoption estimates makes it difficult to compare CSA adoption outcomes across contexts.

A major contribution of this study, therefore, is the development of a typology of farm-level CSA practices to enhance an understanding of CSA adoption among smallholder farm households in rural areas of developing countries. The typology, which developed from a rich theoretical underpinning, comprised of six categories including: (1). residue addition and retention, (2). non-woody plants, (3). assisted natural regeneration, (4). woody plants, (5). physical infrastructure, and (6). mixed measures.

From the typology, we generated testable hypotheses and used primary survey data from a USAID-funded development intervention that promoted CSA practices in southern Malawi as a case study for empirically applying the typology. The program, Wellness and Agriculture for Life's Advancement (WALA) comprised a US$86million that was an integrated food security project including the promotion of CSA adoption in the intervention areas. Using a recursive bivariate probit (RBP) model, we estimated the adoption of CSA categories under the WALA project in line with our farm level typology of CSA categories. The primary data under WALA corresponds coincided with four of the six CSA categories above, including non-woody plants, assisted natural regeneration, woody plants, and physical infrastructure,

We found positive and statistically significant effect of program participation on CSA adoption across the typology. We specifically estimated the marginal effects and average treatment effects of program participation (i.e., average treatment effect on the treated – ATT) on the adoption of individual CSA categories that WALA promoted. The marginal effects of program participation are 12%, 36%, 45%, and 43.2% for non-woody plants, assisted regeneration, woody plants, and physical infrastructure, respectively. Similarly, the ATT of program participation are 41% for non-woody plants, 49% for assisted regeneration, 61% for woody plants, and 94% for physical infrastructure.

The positive and statistically significant effects of the marginal effects and the ATTs of program participation confirmed our first hypotheses that the adoption of various CSA categories depend significantly on participation in the WALA program. Likewise, the incremental differences between the marginal effects and ATT of program participation across the four CSA categories confirms our hypothesis that participation in the CSA intervention under WALA enhanced the adoption of resource-intensive CSA categories that would otherwise, not be adopted due to resource constraints and the heavy transactions costs of these practices.

These estimates imply that under an externally supported CSA intervention such as the WALA CSA development program, adoption rates are higher for resource-intensive CSA categories. Such interventions can lower the transaction costs of CSA adoption for the smallholder farmers, thereby making adoption of CSA practices more attractive in contexts where the bulk of the farming population is constrained by critical resources including labor, capital, and information.

Therefore, our study makes significant contributions to the literature on CSA and to the technology adoption literature in general by developing a farm-level typology of CSA practices, which lends conceptual clarity to CSA adoption, and highlights the effects of external funding on the categories of CSA practices adopted. The study also has significant development policy implications for enhancing efficiency in the allocation of climate adaptation and CSA-related aid by idenitying adoption dynamics of CSA based on resource intensiveness. Understanding such adoption dynamics could better inform development policy on aid allocation for CSA. For example, future climate financing could be directed toward more resource intensive CSA categories in areas where such CSA practices are lacking. It could also guide development practitioners in the allocation of scarce resources for CSA programs at the farm and community level in the developing world.

Future research needs include analyses of: (a). CSA adoption heterogeneity and the impacts of such adoption heterogeneity on food security outcomes (such as crop yields, household incomes), (b). environmental conservation and sustainability outcomes (such as soil health), (c). general welfare impacts of CSA adoption by CSA category. Furthermore, an important research need would be to analyze the various pathways through which CSA program participation impacts food security and environmental conservation. For instance, does an agroforestry adoption under CSA constitute a pathway for the impact of CSA? Such analyses could provide better understanding of CSA in the face of climate change, environmental degradation, and rising global food insecurity.

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CHAPTER 3:

FOOD SECURITY IMPACTS OF CLIMATE-SMART AGRICULTURE IN THE PRESENCE OF AN AID-FUNDED INTERVENTION IN SOUTHERN MALAWI[9]

Abstract

Climate-smart agriculture (CSA) is an increasingly popular approach for adapting agriculture to climate change while also mitigating climate change by sequestering carbon that would otherwise be released into the atmosphere. As such, CSA adoption is vital for sustainable development goals not least relating to food security. However, weak financial capacity in most developing countries including those in Sub-Saharan Africa limits required investments to support CSA so that rural communities remain vulnerable to the effects of climate change. International aid for CSA has helped fill this financing gap with billions of dollars committed toward climate adaptation (including CSA) in the past decade. The impacts of this financial support on food security remain little known, however. Here we use data from a recent USAID-funded intervention that promoted CSA in southern Malawi as a case study to determine food security impacts of external aid through CSA adoption. We use endogenous switching regression to account for unobserved heterogeneity between CSA adopters and non-adopters, using primary survey data from 808 households across five districts in the region. We find positive and statistically significant impacts of CSA adoption on agricultural yields and household income by 90% and 41%, respectively. The findings show that externally-supported CSA interventions can succeed in boosting food security and household welfare and suggest the importance of further CSA investments in similar contexts elsewhere in Africa and beyond.

[9] Thi paper is in revision for submission to a journal

Keywords: adoption, average treatment effects, climate-smart agriculture, endogenous switching regression, Malawi, watershed development.

3.1 INTRODUCTION

Climate-smart agriculture (CSA) has become popular as an approach that enhances sustainable agriculture in the face of climate change, extreme weather shocks such as droughts, and increasing global demand for food (FAO, 2016; Kpadonou et al., 2017; Torquebiau et al., 2018). CSA constitutes climate-sensitive agriculture, consistent with sound environmental management practices (Chandra et al., 2017a; FAO, 2010; Lipper et al., 2014). It adapts agriculture to climate change, mitigates adverse effects of agriculture on the environment through carbon sequestration, and enhances food security through yields (Karlsson et al., 2018; Kearney et al., 2017; Lal et al., 2015; Torquebiau et al., 2018).

CSA is multifaceted and context specific, encompassing farm level, communitywide landscapes, and national level through policy and institutional arrangements (Chandra et al., 2018; FAO, 2016; Jayne et al., 2018; Lipper et al., 2014). It is widely captioned as a broad field that includes integrated agriculture, soil and water conservation, and sustainable land management practices. Examples include agroforestry (Blaser et al., 2018; Mbow et al., 2014; Pardon et al., 2017), conservation agriculture (Chandra et al., 2018; Dhehibi et al., 2017; Liebig et al., 2017; Sommer et al., 2018), and physical infrastructures such as boreholes, contour terraces, and stone bunds (Kpadonou et al., 2017; Lipper et al., 2014; Sain et al., 2017).

Despite its relevance, however, CSA adoption is expensive and generally unaffordable by smallholder farmers in developing countries (Chandra et al., 2018; Karlsson et al., 2018; Sain et al., 2017). Adoption rates are particularly low in Sub-Saharan Africa (SSA) due to binding resource constraints (Cordingley et al., 2015; Gebremariam & Tesfaye, 2018; Jayne et al., 2018). Thus, experts (FAO, 2010, 2013, 2016; Karlsson et al., 2018) argue that increased CSA adoption requires external aid and public sector financing to reduce transactions costs among poorer communities. Both public goods (Aggarwal et al., 2018; Engel & Muller, 2016; Eory et al., 2018; Gebremedhin & Swinton, 2003) and environmental justice perspectives (Adger et al., 2017; Chandra et al., 2017b; Karlsson et al., 2018; Weiler et al., 2018) support such investments.

Recognition of the need for CSA support has helped spur a major increase in global financing of climate adaptation and resilience programs as a sustainable development strategy in developing countries (Dinesh et al., 2017; Weiler et al., 2018; World Bank, 2015). Such global investments could climb to US$100 billion by 2020 (Dinesh et al., 2017; World Bank, 2017). It would be particularly vital for increasing the impacts of CSA such as food security through agricultural yields and household income in diverse areas of SSA, such as southern Africa, where recurrent droughts and food insecurity shocks are common (Sesmero et al., 2018; Ubilava, 2018; World Food Programme, 2017). Malawi is among many countries in SSA, and southern Africa in particular, wherein climate adaptation, mitigation, and food security programs have received large amounts of development aid (Amadu et al., 2018; Arslan et al., 2015; Dinesh et al., 2017) and public-sector spending (Jayne et al., 2018; Manda et al., 2016; Thierfelder et al., 2017).

A growing body of literature on CSA covers the adoption of various CSA practices, and the impacts of such CSA adoption on key outcomes including food security among others. Specific examples of such literature on CSA adoption include Gebremariam and Tesfaye (2018) in Ethiopia, Kpadonou et al. (2017) in West Africa, and Amadu et al. (2018) in Malawi. Examples of literature on the impacts of CSA adoption on crop yields include Arslan et al. (2015) in Zambia, Asfaw et al. (2016) in Malawi, and Smethurst et al. (2017) in Kenya and

Malawi. Welfare impacts of CSA have been studied by Amare et al. (2012) in Tanzania, Manda et al. (2017) in Zambia, and Jaleta et al. (2018) in Ethiopia.

However, there is a dearth of empirical analyses of CSA adoption and impacts (in terms of crop yields and household incomes) that are generated specifically through aid-funded climate adaptation programs that promote CSA in SSA. Analyses of aid-funded climate adaptation exist. For example, Addison et al. (2011), Aggarwal et al. (2018), and Huang and Wang (2018) provide general reviews of various funding schemes and their effects on diverse aspects of climate adaptation and mitigation. Nevertheless, such studies do not analyze the impact of CSA adoption on food security outcomes of smallholder farmers across drier terrains, such as those in southern Africa.

The goal of this paper is to estimate the impact of CSA adoption on agricultural yields and household income as measures of food security in the presence of an external aid that promotes CSA in southern Malawi using observational data. This study seeks to answer the following questions:

- Did a large-aid CSA intervention programs enhance CSA adoption among smallholder farmers in rural SSA such as southern Malawi?
- Does the adoption of CSA increase crop yields and household incomes and thereby food security smallholder farmers in southern Malawi?
- Which factors determine CSA adoption and food security in southern Malawi?

The paper makes several important contributions. First, it provides an initial first step toward narrowing the gap in the literature for empirical evidence on the impacts of externally funded CSA interventions on food security. Second, it contributes to development policy debate in that it highlights the effectiveness of aid-funded CSA interventions in SSA and elsewhere. This is important, because in the face of increasing global climatic shocks, understanding the impacts of large aid programs that promote CSA will enhance food security in countries that heavily depend on agriculture and limited natural resources (Kpadonou et al., 2017; Taylor, 2018; Torquebiau et al., 2018). Such countries include Malawi, which rely almost exclusively on rain-fed agriculture amidst uncertain weather conditions, thereby being highly vulnerable to climate shocks (Coulibaly et al., 2017; Etshekape et al., 2018; Thierfelder et al., 2017). For instance, recent studies (FAO et al., 2017; Gebremariam & Tesfaye, 2018; Jaleta et al., 2018) indicate that acute food insecurity among the poorest communities in SSA and other developing regions remains a critical development challenge despite huge development financing.

The analyses in this paper center on a development project funded by the United States Agency for International Development (USAID). The project, Wellness and Agriculture for Life Advancement (WALA), which promoted CSA practices through a set of watershed development initiatives across rural communities in southern Malawi. WALA was a US$86 million integrated food security project implemented from 2009 to 2014 with several components, including climate adaptation and resilience building, henceforth CSA (Reichert, 2014; Soroko et al., 2018; Verduijn et al., 2014).

Section 3.2 of this paper presents a brief literature review and further motivates the study. It also describes the WALA project and the context of the study area in southern Malawi. In Section 3.3, we present the analytical framework. Section 3.4 presents the estimation results and discussion, while Section 3.5 concludes.

3.2 LITERATURE REVIEW AND BACKGROUND INFORMATION

While the impacts of climate change are global, localized impacts in various regions such as SSA, constitute a major development challenge (Aggarwal et al., 2018; FAO, 2016; Gebremariam & Tesfaye, 2018; Tesfamariam et al., 2018). For example, southern Africa was recently hit by a heavy drought driven by El Niño weather patterns that lingered for the 2014/2015 and 2015/2016 growing seasons, thereby adversely affecting food security in the region (Ubilava, 2018; World Bank Malawi Office, 2016). The drought reduced maize production for the region as a whole by 12% and 26% in the consecutive farming seasons (World Food Programme, 2016, 2017). The country-level reductions were even more dismal, with Malawi's decline at 21% in 2014/2015 and 42% in the 2015/2016 (World Food Programme, 2017). Such shocks further justify the need for CSA, which is designed to improve agriculture's adaptive capacity to climate change and extreme weather shocks while also helping to mitigate agriculture's adverse effect on climate change (e.g., Aggarwal et al., 2018; Arslan et al., 2015; Lipper et al., 2014).

Several researchers such as Amadu et al. (under review), Arslan et al. (2015), and Chandra et al. (2018) touch on the adoption, impacts, and policy implications of CSA in terms of food security and human development. However, most studies do not analyze the impact of CSA adoption in the context of an aid-funded intervention that promotes CSA, as in our study.

For instance, Amadu et al. (under review) provide a typology of farm-level CSA practices in Malawi to aid the analysis of adoption estimates at the farm level of smallholder households and communities in the developing world, using SSA, and southern Malawi in particular, as a case study. Using the farm-level typology, Amadu et al. (under review) analyze the effect of participation in an aid-funded CSA program that promotes CSA interventions on

CSA adoption probability dynamics. They find that participation in aid-funded CSA interventions increases the adoption probabilities of resource intensive practices compared to less resources ones. However, Amadu et al. (under review) do not analyze the impact of the CSA aid intervention on agricultural yields and household incomes of participating households.

Similarly, Arslan et al. (2015) use Zambia's *Rural Incomes and Livelihoods Surveys* with a mix of climate variables to estimate food security impacts of conservation agriculture in Zambia and find statistically significant impacts across a range of contexts. However, they do not analyze food security impacts of CSA within the context of an aid-induced CSA adoption. Aggarwal et al. (2018) assess the impact of the climate-smart village (CSV) concept in the context of CSA adoption and impacts in different parts of the world, including SSA. They find significant effects of the CSA paradigm on soil nutrient management and crop yields among others, suggesting that the CSA approach is an important climate adaptation technique for enhancing agricultural development and environmental sustainability. However, they do not specifically evaluate CSA adoption and resulting impacts in the context of an aid-induced development program that promotes CSA adoption in a localized setting in SSA.

This paper addresses this gap in the literature by analyzing the impact of CSA adoption on food security (through crop yields and household incomes) in the presence of an US$86 million program that had a strong CSA component in southern Malawi. The paper lies at the intersection of several strands of literature including the growing body of knowledge on agricultural technology adoption (e.g., Besley & Case, 1993; Gebremariam & Tesfaye, 2018; Kassie et al., 2015) in drier areas such as SSA, and food security impacts of climate adaptation (e.g., Abdulai, 2016; Coulibaly et al., 2017; Jaleta et al., 2018).

A major departure of this paper from prior studies is that it focuses on food security impacts of CSA adoption in the context of an aid-funded intervention that promoted CSA. Here we analyze the impact of an aid-induced CSA adoption on maize yields and household incomes, through a large USAID project—WALA, described above as being devoted to the reduction of food insecurity in certain communities of southern Malawi (Reichert, 2014; Soroko et al., 2018; Verduijn et al., 2014).

Moreover, this study contributes to development aid policy by shedding light on the efficient allocation of climate adaptation funds in drier regions, including rural areas of SSA. For example, because maize is the staple crop in Malawi, its productivity is an important indicator of two food security indicators: availability and access (Asfaw et al., 2016; Koppmair et al., 2017a; Radchenko et al., 2018; Ragasa & Mazunda, 2018). Therefore, an analysis of food security arising from an externally funded CSA program is important for understanding development policy in terms of CSA financing, environmental conservation, and food security in drier areas such as Malawi.

The paper also advances empirical knowledge by utilizing observational data to conduct impact assessment without a preexisting baseline data, by using endogenous switching regression (ESR) to control for the potential endogeneity of CSA adoption among program participants in the research setting. Several studies (Gertler et al., 2011; Koppmair et al., 2017b; Nichols, 2007) show that without a baseline data, analyzing potential impacts of development programs such as externally promoted CSA on development impacts such as food security using observational data is often difficult because of the potential endogeneity of technology adoption in the presence of aid programs. One could either overestimate or underestimate the impacts due to unobserved factors that may be confounders (Gertler et al., 2011). For example, the impact of CSA adoption could be overestimated if farmers with higher production capacities are also more likely to adopt CSA practices. Conversely, we might underestimate the impact of CSA adoption if low yield capacity and low-income–oriented farmers are more likely to adopt.

Several studies (Abdulai, 2016; Jaleta et al., 2018; Noltze et al., 2013) utilize ESR as an efficient analytical method for impact assessments in contexts without baseline data. The ESR divides farmers across the research setting into two categories: adopters and non-adopters based on farmers' classifications, thereby enhancing an analysis of the outcomes of the two categories (Abdulai, 2016; Coulibaly et al., 2017; Tesfamariam et al., 2018).

We test two hypotheses:

> ***H1:*** *Various socioeconomic and biophysical factors explain variation in participation in an externally funded CSA program, CSA adoption, and its impacts on food security in southern Malawi.*

Biophysical factors include house elevation, slope of the land, distance to the nearest main road, distance to an Agricultural Development and Marketing Corporation (ADMARC), distance to a treated watershed, as well as distance to an extension office. We expect longer distances to the market and an extension agent's office to negatively affect CSA adoption due to higher transaction costs (Key et al., 2000; Khonje et al., 2015; Manda et al., 2016).

> ***H2:*** *CSA adopters will have higher food security outcomes, including agricultural yields and household income, through consumption spending compared to non-adopters.*

Similar prior studies (Abdulai & Huffman, 2014; Coulibaly et al., 2017; Jaleta et al., 2018) show that adopters of various agricultural technologies realize higher outcomes (including yields and farm incomes) than non-adopters.

3.2.1 Country context and the WALA project – southern Malawi

Malawi's socioeconomic and biophysical characteristics, such as high population density and environmental degradation through deforestation pose serious threats to the country's development (Coulibaly et al., 2015; Dougill et al., 2017; World Bank Malawi Office, 2017). For instance, current population estimate stands at 17.2 million with a population density of 183 per square kilometer, with the southern region being the densest, with 46% of the national population, while 12% reside in the northern region (National Statistical Office of Malawi, 2017b). Total fertility stands at 4.4 children per woman, with an under-five mortality rate of 63 deaths per 1000 live births. Poverty and food security indicators are dismal. For instance, recent estimates show that 33% of women ages 15–49 years and 63% of children between 6 and 59 months are anemic. Moreover, 37% of under-five children are classified as stunted, 3% as wasted, 12% as underweight, and 5% overweight (National Statistical Office of Malawi, 2017a,b).

In Malawi, smallholder farmers account for about 70% of agricultural output, while large-scale producers account for 30% (Coulibaly et al., 2017; Ragasa and Mazunda, 2018). Maize is the main staple crop, having a national per capita consumption of about 133 kg (Mussa, 2015). However, production levels are generally low with a national average of about 2.1 tons per hectare in 2013, with wide variability across different parts of the country (Komarek et al., 2017).

To overcome long-standing poverty due to high environmental degradation in southern Malawi, USAID funded a US$86 million integrated food security project under its "Food for Peace" program as a multi-year Title II project. The WALA project spanned eight districts in southern Malawia with the goal of enhancing food security among vulnerable households in the project area (Reichert, 2014; Soroko et al., 2018). Figure 3.1 presents the eight districts of Balaka, Chikwawa, Chirazulu, Machinga, Mulanje, Nsanje, Thyiolo, and Zomba, which were selected because they were deemed highly vulnerable to food insecurity through harsh biophysical conditions (such as massive environmental degradation), and socioeconomic factors including high population density and rural poverty (Reichert, 2014; Soroko et al., 2018; Verduijn et al., 2014).

WALA's theory of change comprised food security attainment through the adoption of various CSA practices, with the notion that CSA adoption enhances improved soil moisture through erosion control and prevention of nutrient depletion among other environmental benefits (Reichert, 2014; Soroko et al., 2018; Verduijn et al., 2014). Therefore, CSA intervention, through watershed development, was central to WALA's operations. It comprised training farmers to adopt CSA as part of their communities' environmental management and livelihood enhancement approach. WALA provided group training on natural resource management practices such as conservation agriculture (CA) and water catchments management at the community level, wherein individual farmers who participated received some incentive such as food for assets. The specific practices through which WALA provided CSA training included agroforestry, apiculture, check dams, continuous contour trench (CCT), stone bunds, marker ridges, vetiver grass, and water absorption trench (WAT). The goal was to ensure that individual farmers adopt these practices as a suite of CSA package techniques on their farms, resulting in food security (Reichert, 2014; Soroko et al., 2018).

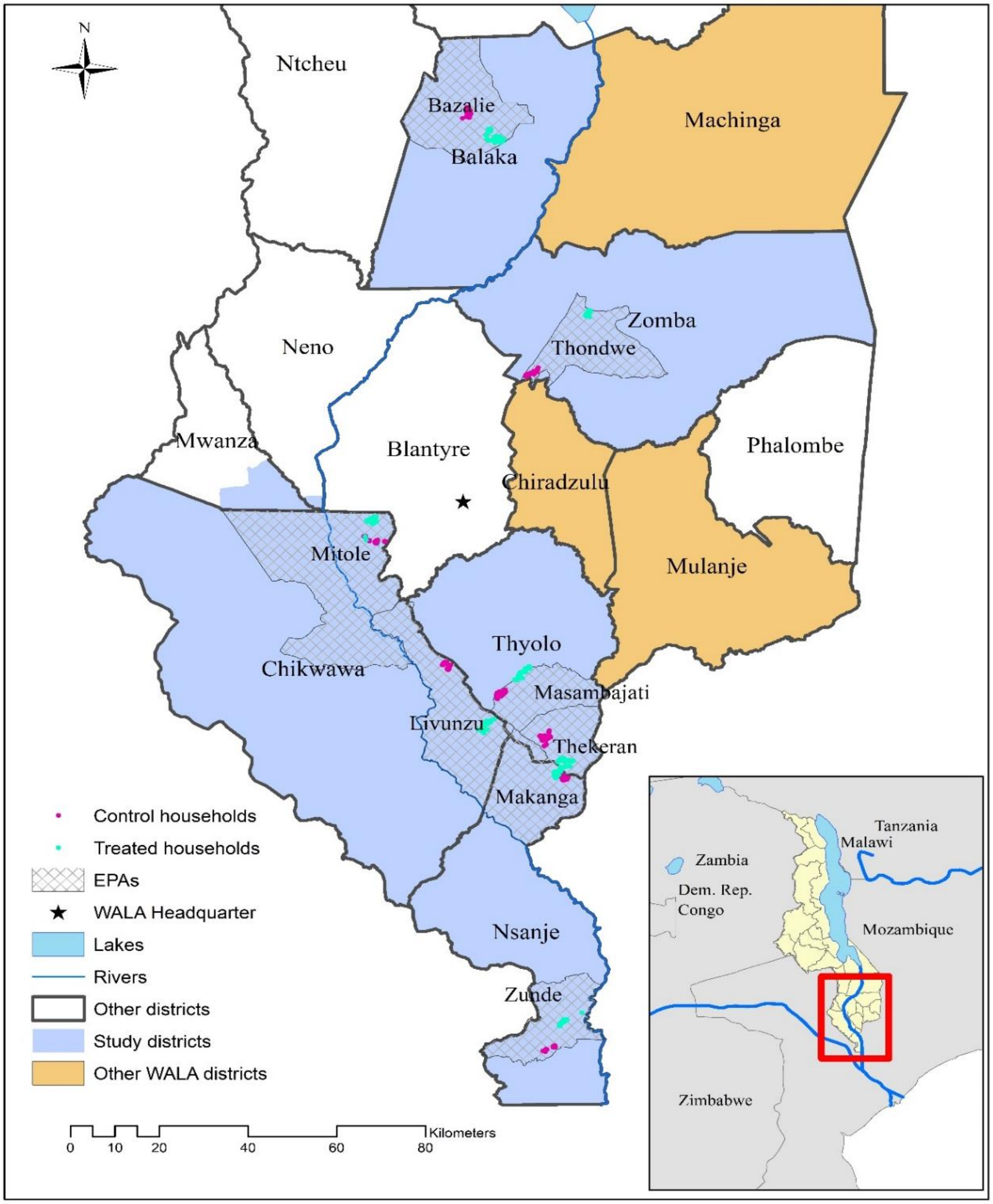

Figure 3.1: Study area showing treated and control households within districts (*Source*: Amadu et al., under review).

3.3 ANALYTIC FRAMEWORK AND ECONOMETRIC APPROACH

3.3.1 Conceptual framework for the impact of CSA adoption

The definition of CSA adoption in this study comes from Amadu et al. (2018).[10] Accordingly, CSA adopters are farmers in the WALA project area who received training about CSA either directly from WALA staff, or from its affiliates, and who have been implementing at least one CSA practice on their farms following such trainings from 2012 (when WALA had reached all communities with CSA) to 2016 (when data collection occurred). However, we assume that not everyone in the treatment areas may adopt CSA in as much as not everyone who adopted CSA may be resident in the treatment area (Noltze et al., 2013). Due to the diffusion of innovation, it is possible for people outside of the WALA intervention areas to receive CSA knowledge either directly from social learning, or from self-selecting into the adopter categories by trying out the technology on their own, especially if they reside in close proximity to a treatment community (Rogers, 2003). Subsequently people outside the project intervention zones who somehow adopted CSA may have similar outcomes as adopters who resided in the intervention areas. Conversely, those outside the intervention areas who adopted CSA may have higher outcomes than those in the treatment areas who failed to adopt.

Figure 3.2 illustrates the conceptual framework for this study, showing the possibility of CSA adoption across treatment and control areas due to for example, diffusion of innovation and social learning, as the extant literature suggests (e.g., Kabunga et al., 2012; Noltze et al., 2013; Rogers, 2003). We assume potential diffusion of innovation across GVH boundaries. In

[10] This study uses the same primary survey data used in Amadu et al. (under review), and extends the analyses therein to the impacts of CSA adoption on food security in the same context. It is, therefore, prudent to use similar definition of CSA adoption across the two papers.

particular, we assume that households outside a WALA GVH could adopt CSA either through participation in CSA training across GVH boundaries as a means of obtaining the FFA that WALA provided to participating households (see section 1.5 and figure 1.2 in the introduction (see section 1.5 above) or though mere learning from other farmers. Therefore, it is possible for the post-WALA intervention period to have both adopters and non-sdopters as in Figure 3.2.

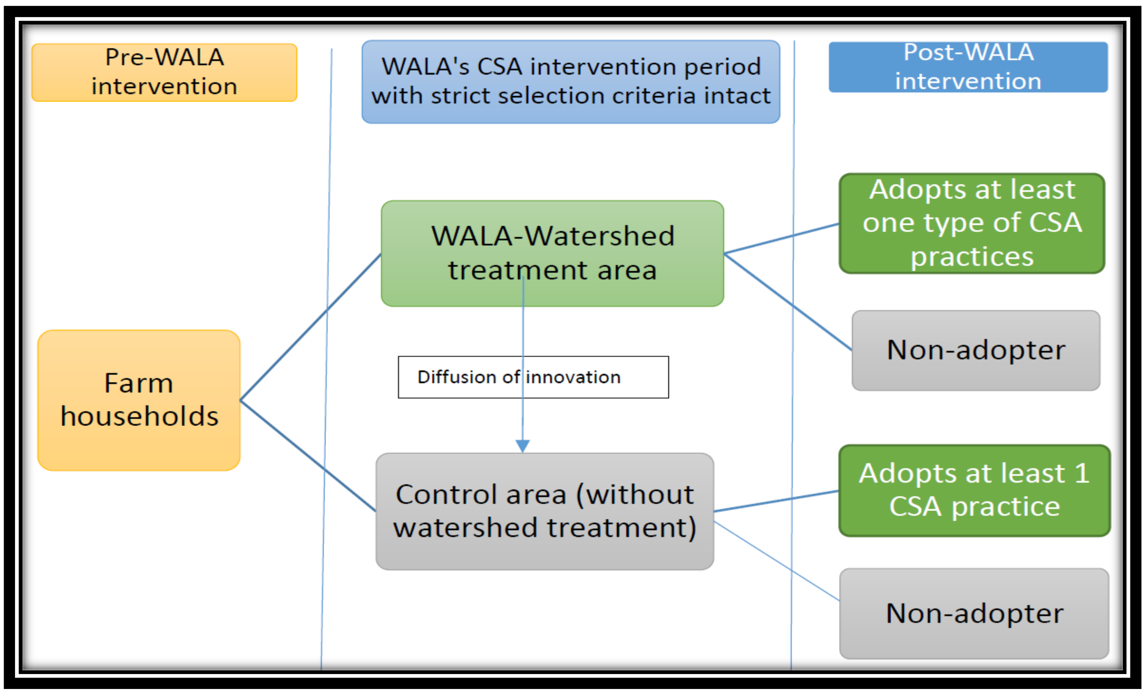

Figure 3.2: Conceptual framework for the quasi-experimental analysis in this study

We use two standard methods to study food security in terms of yields and incomes. First, it operationalizes the standard Cobb-Douglas production function, which specifies the link between agricultural outputs such as maize yields with farm inputs such as labor and fertilizer (Battese, 1997; Kabunga et al., 2012; Kahsay & Hansen, 2016; van Dijk et al., 2017) to estimate yield functions. Second, it uses the non-severability theory of the farm household (Amare &

Shiferaw, 2017; de Janvry & Kanbur, 2006; Singh et al., 1986; Smale & Mason, 2014) to estimate the household incomes of farmers in the research setting.

In particular, following Kahsay and Hansen (2016) and Noltze et al. (2013), we specify one functional form for both the maize yield and household income (in terms of consumption spending) equations as follows:

$$Y_{ym} = (L, K, B), \tag{3.1a}$$

where Y_{ym} is maize yield and household income, L constitutes labor, K is capital including household endowments and social network, B is a set of biophysical factors such as slope, fertility of the land, and distance to a watershed that has been developed. We operationalize equation (1a) into the standard Cobb-Douglas function model as

$$Y_{ym} = L^{\alpha_{1i}}\, K^{\alpha_{2i}}\, B^{\alpha_{3i}}, \tag{3.1b}$$

where $\alpha_{1i}, \alpha_{2i}, \alpha_{3i}$ are parameters, and Y_{ym}, L, K, B are as defined earlier.

We use cross-sectional data due to a lack of panel data, which is a common challenge in ex-post impact studies such as the present study. However, our econometric method is robust enough to capture the effect of CSA adoption on yield and income even in the absence of panel data (Noltze et al., 2013; Terza, 1999; Tesfamariam et al., 2018).

3.3.2 Empirical strategy

Ideally, if we had complete information about farmers in this setting, and if they had been randomly assigned into CSA adopter and non-adopter categories, we could have easily partitioned their outcomes into two groups: one for adopters and another for non-adopters. Then we could have estimated the impact of adoption by simply taking the difference in mean outcomes between the adopters and non-adopter groups. This is the concept of the average treatment effect (ATE) (Gertler et al., 2011). For policy, we would like to know the impact of a program on those who actually participated in that program; that is, the average treatment effect on the treated (ATT). In addition, if we are interested in knowing the impact on those who did not participate, we estimate the average treatment effect on the untreated (ATU) (Gertler et al., 2011). However, we do not have complete information about farmers in this setting. Moreover, there was no random assignment into adopter and non-adopter categories. Farmers self-selected into the two groups based on their perceived benefits of CSA adoption and other characteristics, some of which we can observe, such as their capital endowment, land sizes, and their decisions to hire labor (Abdulai, 2016; Abdulai & Huffman, 2014). There are potentially unobserved factors that may also influence their adoption or non-adoption decisions, which we as researchers do not know (Abdulai & Huffman, 2014; Tesfamariam et al., 2018).

For example, unobserved factors such as motivation could simultaneously influence CSA adoption decision and resulting impacts. As such, CSA adopters may be systematically different from non-adopters, which could influence their adoption decisions and, thus, the impact on food security (Coulibaly et al., 2017; Noltze et al., 2013). Ignoring such potential endogeneity in CSA adoption decisions and the impacts on yield and income will result in biased estimates and flawed policy recommendation (Abdulai, 2016).

Empirical methods for analyzing the impact of interventions through observational data include propensity score matching (PSM), which uses observed differences between adopters and non-adopters to create an artificial control group for the counterfactual (Rosenbaum & Rubin, 1985). PSM relies on the strong assumption of ignorability (or conditional independence), which, however, does not account for unobserved differences between the treatment and control units (Abdulai & Huffman, 2014; Coulibaly et al., 2017; Tesfamariam et al., 2018).

Other estimation methods include instrumental variable (IV) techniques that control for unobserved differences. However, the IV techniques are also fraught with the limitations of model specification and structural form requirements. A more efficient method is the endogenous switching regression (ESR), which is another form of IV but without the function form requirement imposed by traditional IV techniques (Abdulai, 2016; Jaleta et al., 2018; Tesfamariam et al., 2018).

Lee (1982) was the first to develop the ESR approach as a generalized framework for the Heckman selection correction technique (Abdulai & Huffman, 2014). It accounts for unobserved heterogeneity and selection bias, by estimating two different outcome equations, one for adopters, and another for non-adopters, conditional on their selection into treatment (Abdulai & Huffman, 2014; Coulibaly et al., 2017; Tesfamariam et al., 2018), which in this case is CSA adoption.

The ESR technique applies a two-stage framework. First, there is a selection equation, which utilizes a binary choice procedure to isolate farmers into the adopter and non-adopter categories based on their classification. That is, farmers are classified as adopters and non-adopters based on our definition of CSA adoption above. The main function of the selection equation is to highlight unobserved differences between adopters and non-adopters, which could otherwise bias the impact in question (Kabunga et al., 2012; Lee, 1982; Noltze et al., 2013). Its role is not to merely explain the determinants of adoption even though it does so. Therefore, to ensure proper identification in the estimation process, we should ensure that at least one variable in the selection equation is excluded from the outcome equations (Abdulai, 2016; Kabunga et al., 2012; Lokshin & Sajaia, 2004; Tesfamariam et al., 2018).

Applying the random utility framework in which the farmer evaluates the benefits of

CSA adoption to inform his/her decision of whether to adopt CSA practices or not, we specify our selection equation in the first stage of the switching regression as

$$A_i^* = \pi Z_i + \xi_i \text{, with } A_i = \begin{cases} 1, & if\ A^*{}_i > 0, \\ 0, & Otherwise \end{cases} \tag{3.2}$$

where A_i^* is a vector of the binary latent variable representing the utility of CSA adoption to the farmer, and A_i is a vector of the binary dummy for the CSA adoption equation in which the farmer chooses whether to adopt CSA or not, based on his/her household and biophysical characteristics and other factors. π is a vector of parameters, while ξ is an error term with zero mean and constant variance (Coulibaly et al., 2017; Kabunga et al., 2012). In the second stage, we specify two regimes for each of the food security outcomes under consideration. These include yield effect and household income effects. Based on the conceptual framework above, we state the relationship between each of the outcome (Y) and a vector of covariates as a set of two-regime equations:

$$Y_{1i} = \beta_1 X_{1i} + \mu_{1i} \text{, if } A = 1 \text{ and} \tag{3.3}$$

$$Y_{0i} = \beta_0 X_{0i} + \mu_{0i} \text{, for } A = 0 \text{ ,} \tag{3.4}$$

where Y_{1i} and Y_{0i} denote maize yields, and incomes for CSA adopters & non-adopters respectively. β_1 and β_0 are parameters to be estimated, the variable X_i denotes exogenous characteristics of farmers in the corresponding regimes and Z_i is a vector that determine the regime switching in the system and contains at least one variable that is not in X.

The three error terms μ_{0i}, μ_{1i}, and ξ_i are assumed to be jointly normally distributed with zero mean, and a covariance matrix that is non-singular. We express the covariance matrix as

$$\text{Cov}\ (\xi_i, \mu_{0i}, \mu_{1i}) = \begin{bmatrix} \sigma_1^2 & \sigma_{10} & \sigma_{1\xi} \\ \sigma_{10} & \sigma_0^2 & \sigma_{0\xi} \\ \sigma_{1\xi} & \sigma_{0\xi} & \sigma_\xi^2 \end{bmatrix}, \tag{3.5}$$

where σ_1^2 = var(μ_1), σ_0^2 = var(μ_0), σ_{10} = cov($\mu_1.\mu_0$), $\sigma_{1\mu}$ = cov($\mu_1.\xi$), and $\sigma_{0\xi}$ = cov($\mu_0.\xi$). It is standard to assume that σ_ξ^2 = 1 because Y_{0i} and Y_{1i} are not simultaneously observed (Di Falco et al., 2011; Kabunga et al., 2012; Lokshin & Sajaia, 2004; Tesfamariam et al., 2018). Therefore, the expected values of the error terms in equations (3.3) and (3.4) are zero, which might yield bias in ordinary least squares (OLS) estimates. The truncated error terms have the following expected values:

$$E[\mu_{1i}|A_i = 1] = \sigma_{1\xi}\ \lambda_{1i} \quad \text{and} \tag{3.6}$$

$$E[\mu_{0i}|A_i = 0] = \sigma_{0\xi}\ \lambda_{0i} \tag{3.7}$$

where

$$\lambda_{1i} = \frac{\phi[\pi Z_i]}{\Phi[\pi Z_i]}, \text{and } \lambda_{0i} = \frac{\phi[\pi Z_i]}{1-\Phi[\pi Z_i]}.$$

ϕ is the standard normal probability density function, and $\boldsymbol{\Phi}$ is the standard normal cumulative density function (CDF). The parameters, λ_{1i} and λ_{0i} conditional on the selection equation constitute the "inverse Mills ratios (IMRs) (Abdulai & Huffman, 2014; Noltze et al., 2013). Usually, the two-stage estimation of switching regressions use the IMRs in the regime switching equations. This two-stage procedure of the estimation process has the limitation of generating residuals that are heteroscedastic. A recent and widely used approach, the full information maximum likelihood (FIML) proposed by Lokshin and Sajaia (2004), performs a simultaneous equation system to obtain efficient parameter estimates of the selection and outcome models in the system (Coulibaly et al., 2017; Kabunga et al., 2012). Hence, we use the endogenous switching regression with the FIML procedure.

By FIML, we estimate the correlation coefficients of the outcome equation (i.e., β_0 and β_1), and the correlation coefficients between the stochastic terms in the selection and outcomes models. That is, $\rho_1\xi$ and $\rho_0\xi$ (Abdulai & Huffman, 2014; Kabunga et al., 2012; Lokshin & Sajaia, 2004).

Accordingly, there is endogenous switching if either of $\rho_1\xi$ and $\rho_0\xi$ statistically significantly different from zero. For example, if $\rho_1\xi > 0$, then there is negative selection bias in CSA adoption, meaning farmers with below-average yields are more likely to adopt CSA, whereas, $\rho_1\xi < 0$ implies positive selection bias (Coulibaly et al., 2017; Kabunga et. al, 2012). Moreover, if $\rho_1\xi$ and $\rho_0\xi$ have opposite signs, then CSA adoption is by comparative advantage (Coulibaly et al., 2017). However, if $\rho_1\upsilon$ and $\rho_0\xi$ have the same sign, it implies that both adopters and non-adopters are better off in their respective decision outcomes of adopting or not adopting, given their present levels of yield potential and household income.

In addition to accounting for potential selection bias in the adoption and impact of CSA practices in southern Malawi, the ESR attributes the impact of WALA in terms of the CSA practices it promoted, based on the program's target outcome of food security. To that end, we can definitively estimate the effects of CSA adoption on yield per acre for maize, the main staple crop, and assess the income effect through household expenditure on it. We compare the mean yields and incomes of CSA adopters and non-adopters in actual and hypothetical scenarios using the following sets of equations and algorithms, thereby computing the ATTs and ATUs as follows:

- CSA adopters (observed in sample)

$$E(Y_{1i}|A_i = 1, x) = \beta_1 X_{1i} + \sigma_{1\xi}\, \lambda_{1i} \tag{3.8}$$

- CSA non-adopters (observed in sample)

$$E(Y_{0i}\,|A_i = 0, x) = \beta_0 X_{0i} + \sigma_{1\xi}\, \lambda_{0i} \tag{3.9}$$

- CSA adopters, had they not adopted (counterfactual case)

$$E(Y_{0i}\,|A_i = 1, x) = \beta_0 X_{1i} + \sigma_{0\xi}\, \lambda_{0i} \tag{3.10}$$

- Non-adopters of CSA, had they adopted (counterfactual case)

$$E(Y_{1i}|A_i = 0, x) = \beta_1 X_{0i} + \sigma_{1\xi}\, \lambda_{1ii} \tag{3.11}$$

- Effect of CSA adoption on yields of adopters (ATT)

ATT = equation (3.8) – equation (3.10)

$$= E(Y_{1i}|A_i = 1, x) - E(Y_{0i}|A_i = 1, x)$$

$$= X_{1i}(\beta_1 - \beta_0) + \lambda_{1i}\,(\sigma_{1\xi} - \sigma_{0\xi}) \tag{3.12}$$

- Average treatment effect on the untreated (ATU)

ATU = equation (3.11) – equation (3.9)

$$= E(Y_{1i}|A_i = 0, x) - E(Y_{0i}\,|A_i = 0, x)$$

$$= \beta_1 X_{0i} + \sigma 1\xi\lambda_{0i} - \beta_0 X_{0i} + \sigma_{0\xi}\, \lambda_{0i}$$

$$= X_{0i}\,(\beta_1 - \beta_0) + \lambda_{0i}\,(\sigma_{1\xi} - \sigma_{0\xi}). \tag{3.13}$$

Following Noltze et al. (2013) and Abdulai and Huffman (2014), we estimate two sets of different ESR models. The first one accounts for the yield outcome, while the second specification captures the income effect. However, unlike Noltze et al. (2013) we use similar explanatory variables across the two systems, with very slight alterations in the variables. The use of similar variables across the two sets of models is similar to Abdulai and Huffman (2014) in Ghana, who estimated the effect of adopting stone bund technology on yield and income.

The outcome variables we use include adoption status as well as outcomes for maize yields per acre and income. Maize is the staple crop in Malawi. Thus, food security in Malawi depends on its yield, which is an indicator of “availability and access” dimensions of food security for the smallholders in our setting.

Similarly, the household income effect of CSA adoption uses per capita annual consumption spending on maize. We use the reported per capita annual household spending on maize as a proxy for household income because farmers in this setting, as in many developing countries, do not accurately report incomes since they do not have regular income streams. Given that maize is the most important crop in Malawi, and consumed by the bulk of the Malawian population, it is expedient to determine the ability of poor rural households such as those in WALA project areas, to purchase maize. This relates to the affordability and access measures of food security (FAO, 2016).

In both estimations of yield and income, we need an instrumental variable (IV) that can control for endogeneity of CSA adoption in the impact equations since treatment assignment in this study was not random, but adopters self-selected into the adoption category. A valid IV should affect CSA adoption but not the outcome measure directly other than through CSA adoption. To be valid, the IV should be highly correlated with the endogenous variable, CSA adoption in this case, and uncorrelated with the outcome measures, the log of yield per acre and the log of per capita household consumption spending on maize in this case.

We use distance to the nearest Agricultural Extension Development Coordinator (AEDC) office. The distance to an AEDC office is an important measure of farmers' potential access to extension services, which are central to technology adoption. For the yield equation, we use the normal distance, and for the consumption expenditure model, we use the log of distance. In both specifications, the IV is uncorrelated with the outcome variables but highly correlated with the adoption decision.

Table 3.1 shows that these values are plausible. For example, the correlation between CSA adoption and the IV is significantly different from zero in both the normal and log forms (with values of -0.3389*** and -0.3659*** respectively). Conversely, the correlation between the outcomes measures are not statistically different from zero (0). The values are plausible because while we expect distance to an AEDC office significantly affect interaction between farmers and extension agents, there is no reason to believe that such distance should directly affect yields or household consumption indirectly through the adoption decision.

Table 3.1: Validity check for instrumental variables

Outcome variable	Instrumental variable	Correlation coefficient	P-value
Yield per acre (log)	Distance to AEDC office	-0.0208	0.5540
Per capita annual consumption spending	Distance to AEDC office (log)	-0.0459	0.1925
Per capita consumption spending for 60 days	Distance to AEDC office (log)	0.0567	0.1073
CSA adoption	Distance to AEDC office	-0.3389	0.0000
CSA adoption	Distance to AEDC office (log)	-0.3659	0.0000

Note: CSA, climate-smart agriculture; AEDC, Agricultural Extension Development Coordinator

3.3.3 Data

We use primary survey data from a sample of 808 households across the smallholder farmer population in the WALA project area. We categorize farmers into adopters and non-adopters based on their responses to a well-designed survey questionnaire that we created for this study. The questionnaire follows the details described above regarding our definition and measure of CSA adoption in this setting. Thus, although we collected data from communities that received the CSA intervention, and those that did not, we do not expect the spatial boundaries to limit CSA adoption. Not all participants in WALA adopted CSA, and some non-WALA participants adopted CSA practices on their own, probably due to diffusion or spillover. It is standard for project interventions such as the WALA watershed and CSA adoption to have spillover effects (Arndt et al., 2016; Gertler et al., 2011).

Our survey design employs a multistage framework. First, we purposely sampled eight Extension Planning Areas (EPAs) across five WALA districts. Second, we selected two grouped village headman (GVH) communities from each EPA. Third, we randomly selected 15% of the households from each GVH community, which resulted in 808 households surveyed. We put a special emphasis on EPAs, because they coordinate extension services in Malawi.

We collected data from late July 2016 to early September 2016. Data consist of microlevel details of farm households' cropping systems and consumption to that point in 2016 and the 12 months before our data collection. We also collected community-level data through key informant interviews and personal observations. Additionally, we collected secondary data from the WALA project office in Blantyre and AEDC offices.

Field staff for data collection were all Malawian citizens, fluent in the main local languages, including Chichewa. They all received thorough training on administering the questionnaires for this study. Training also included a day of pretesting and several days of feedback loops prior to conducting the actual survey. During the survey, we closely supervised all enumerators to ensure data quality and other important standards. We use the list of households per GVH, which we obtained from WALA project staff and community natural resources management (NRM) groups in the study area to randomly select households for the analyses. We collected household-level, plot-level, and biophysical data such as distance to the AEDCs, to a main all-weather road, and yield of maize in 2016.

3.3.4 Descriptions of variables

We expect certain variables to affect CSA adoption and food security outcomes. These include age (measured in years), gender (a dummy = 1 if female), and education (in years of schooling) of the household head, size of the household, total land size, access to credit, social network size, perception/awareness about CSA, hired labor, number of extension visits, and perception of soil fertility. The literature on agricultural technology adoption and impacts shows that household, plot characteristics, and biophysical factors are important determinants of technology adoption (Arslan et al., 2014; Manda et al., 2016). Certain household-level variables will positively influence CSA adoption and impacts of CSA on yield and income, while others will have negative effects. Variables that will negatively affect CSA adoption and outcomes include off-farm work (though this is sometimes ambiguous, we expect it to be negative here since CSA is labor intensive), credit constraint, labor constraint, and house elevation. Variables that will positively affect CSA adoption and food security impacts include social network and group membership.

Biophysical factors (i.e., plot-level variables) include house elevation, dummy for whether there was drought- or flood-related food aid in the past two years, a dummy for whether the plot is on a steep slope (1 = yes), perception of soil fertility, distance to the nearest AEDC office, and number of CSA practices on the plot, among others. These variables are expected to affect CSA adoption and food security outcomes in positive ways, but they could be negative depending on other factors such as farm management, including labor availability. For example, distance variables could negatively affect CSA adoption, while the other variables positively affect adoption and impacts.

3.3.5 Descriptive statistics

Table 3.2 and Table 3.3 provide descriptive statistics for the main outcome variables and covariates, categorized as household characteristics, plot-level details, and community-level data.

There are noticeable differences between adopters and non-adopters in terms of the main outcome variables, and many of the covariates. For instance, Table 3.2 shows that the yield per acre for adopters is much higher (9.4 bags versus 5.1 bags) with a statistically significant difference at the 1% level. Table 3.2 also shows that adopters are older on average, which might imply a higher level of experience in farming and technology adoption issues that may affect CSA adoption and the outcomes of interest, either directly or indirectly. Other important differences between the two groups include their understanding of CSA, the number of extension visits, and access to capital in the form of fertilizer application and labor hire.

Plot-level differences exist in terms of the perceptions of soil fertility and distances to the watershed and the Agricultural Development and Marketing Corporation (ADMARC), which often sells food grains and inputs at subsidized prices. At the community, differences exist with respect to climate-change impact and the extent of watershed development, which promoted the CSA practices.

Table 3.2: Summary statistics of outcome variables and household-level characteristics

	Adopters, n = 499		Non-adopters; n = 309		Difference
	Mean	**Std. dev.**	**Mean**	**Std. dev.**	
Outcome variables					
Maze yield per acre in 2016	9.368	5.368	5.135	3.243	4.233***
Yield per acre in 2015	16.10	5.557	8.842	4.309	7.255***
Yield per acre in 2014	11.00	5.408	7.462	5.573	3.542***
Per capita annual consumption spending on maize – 2016	9476	8608.267	6948	7468.646	2.5e+03***
Per capita consumption spending, past two months	1340	1272.34	1207	1455.933	1332.2
Household characteristics					
Age of household head (years)	53.010	13.900	38.93	15.957	14.078***
Female headed (dummy)	0.576	0.495	0.553	0.498	0.0230
Household size	9.592	2.538	6.325	3.342	3.268***
Education of household head (years)	10.023	2.801	6.309	4.031	3.714***
Total land size (acres)	2.877	0.951	2.564	0.931	0.313***
Below 2 acres	0.100	0.301	0.156	0.364	-0.056**
2–4 acres	0.828	0.378	0.798	0.402	0.031
More than 4 acres	0.071	0.015	0.040	0.009	0.025
Maize plot size in 2016	2.049	0.842	1.989	0.779	0.061
Maize plot size in 2015	1.834	0.774	1.761	0.703	0.073
Project before WALA	5.676	2.850	5.972	4.215	-0.296
Understand CSA	0.922	0.268	0.267	0.442	0.656***
Off-farm work	0.889	0.315	0.905	0.294	-0.016
Livestock ownership (dummy)	0.476	0.500	0.461	0.499	0.015
Extension visits in 2016	9.359	2.177	5.872	2.611	3.487***
House elevation (meters)	441.078	347.761	492.846	325.434	-51.768**
Distance to nearest ADMARC (km)	16.715	13.525	17.213	12.322	-0.499
CSA-social network	6.751	2.921	3.683	3.912	3.067***
Kin network	4.683	1.452	5.513	5.455	-0.830***
Credit constrained	0.398	0.490	0.435	0.496	-0.037
Labor constrained	0.971	0.168	0.988	0.109	-0.017*
Hired labor (dummy)	0.864	0.343	0.230	0.422	0.634***
Hired labor cost	4250.170	2832.25	3109.49	2227.99	1140.528***
Fertilizer used (kg)	10.052	7.526	8.857	7.315	1.195**

Significance levels: *** < 1%, ** < 5%, * < 10%
Note: WALA, Wellness and Agriculture for Life Advancement; CSA, climate-smart agriculture; ADMARC, Agricultural Development and Marketing Corporation

Table 3.3: Summary statistics of plot and community characteristics

	Adopters, n = 499		Non-adopters, n = 309		Difference
	Mean	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**
Plot-level characteristics					
Plot is steep	0.508	0.501	0.477	0.501	0.031
Plot is flat	0.087	0.283	0.096	0.251	0.009
Walking distance to the main road	41.786	33.813	43.033	30.806	1.247
Perception of soil fertility	0.951	0.215	0.473	0.501	0.479***
Distance to a treated watershed (km)	2.897	3.717	11.775	11.249	8.879***
Distance to nearest AEDC office (km)	8.367	7.162	14.345	8.589	-5.977***
Total CSA practice in past five years (reported)	3.117	1.022	0.911	1.325	2.207***
No. of observed CSA practices	4.663	0.881	2.010	1.908	2.583***
Community characteristics					
Flood- or drought-related food aid	0.693	0.462	9.407	0.500	0.208***
Size of watershed development group	16.795	8.281	0.116	9.343	7.389***
Balaka District	0.104	0.305	0.281	0.321	- 0.013
Chikwawa District	0.282	0.450	0.202	0.451	0.001
Nsanje District	0.194	0.396	0.317	0.402	- 0.008
Thyolo District	0.307	0.462	0.084	0.466	- 0.009
Zomba District	0.113	0.317	9.407	0.278	0.029

Significance levels: *** < 1%, ** < 5%, * < 10%
Note: AEDC, Agricultural Extension Development Coordinator; CSA, climate-smart agriculture

However, prior studies (e.g., Abdulai & Huffman, 2014; Noltze et al., 2013) show that these differences in means may not necessarily explain the impact of the WALA CSA intervention in terms of food security outcomes due of potentially unobserved heterogeneity and selection bias. Therefore, we needed to utilize rigorous multivariate analyses to determine the true impact of the program.

3.4 RESULTS AND DISCUSSION

We use a probit model to estimate the determinants of CSA adoption in the first stage of the ESR and use FIML in the second stage to determine the impact of CSA adoption on yield and income. In both sets of endogenous switching regressions, the FIML technique jointly estimates the adoption and impact equations. Therefore, we jointly present the selection and outcome equations. Tables 3.4 and 3.5 show these estimates, placing the factors that influence farmers' selection decisions into treatment and non-treatment categories, as well as how these factors affect the outcome variables. We explain these outcomes separately below.

3.4.1 Determinants of CSA adoption

The essence of the selection equation in the endogenous switching regression is not necessarily to explain CSA adoption decisions (Kabunga et al., 2012), but to show unobserved differences between adopters and non-adopters, which could bias the impacts generated by the outcome equation. Therefore, we do not spend too much time explaining the determinants of adoption in Tables 3.4 and 3.5 separately. Instead, we focus on the explanation for determinants of adoption in Table 3.4. The second column (labeled as "selection equation") in Table 3.4 shows the determinants of CSA adoption, while columns 3 and 4 show the effects of covariates on yield, for adopters and non-adopters. Columns 3 and 4 are the two regime equations discussed in the endogenous switching regression technique above.

Table 3.4 shows that the major determinants of CSA adoption include farmers' perceptions of CSA in affecting their livelihoods, extension visits, labor, perceptions of soil fertility, and household size. Labor has the highest effect. For instance, our result shows that having the ability to hire labor increases the probability of CSA adoption by about 71%. This finding is consistent with Abdulai and Huffman (2014) in Ghana, and Notlze et al. (2013) in

Timor Leste, who find statistically significant effects of labor availability on the probability of technology adoption.

Moreover, farmers with a positive understanding of CSA are likely to adopt CSA practices with a probability of about 94%. Additionally, the effect of household size is positive and statistically significant, which implies that the probability of CSA adoption increases with household size, a finding that is consistent with previous studies (e.g., Abdulai & Huffman, 2014; Manda et al., 2016). This is probably due to the notion that larger households have a higher prospect of labor endowment, which might affect the adoption probability. Similarly, the effect of extension contacts is statistically significant, which implies that an additional contact with extension agents would increase the probability of CSA adoption by about 8%, a result that is also consistent with the literature on technology adoption.

Furthermore, farmers who have a positive view of CSA as an important factor in their livelihoods through yields and other environmental factors are highly likely to adopt CSA practices, by a probability as much as 94%. This suggests that intensification of CSA awareness campaigns and training on the use of CSA practices are very important for CSA adoption in southern Malawi.

Table 3.4: Endogenous switching regression result for determinants of climate-smart agriculture (CSA) adoption and yield

	Selection equation (Standard error)	**Adopters (Standard error)**	**Non-adopters (Standard error)**
Age of household head (years)	0.00537	0.00104	0.00227
	(0.00458)	(0.00226)	(0.00217)
Female-headed household (1 = yes)	-0.0585	-0.0194	-0.0186
	(0.130)	(0.0626)	(0.0597)
Household size	0.0580*	0.0183	0.00566
	(0.0253)	(0.0127)	(0.0118)
Education of household head (years)	0.0552*	-0.0106	-0.00438
	(0.0228)	(0.0116)	(0.0101)
Perception of CSA effects	0.959***	0.391**	0.416***
	(0.197)	(0.121)	(0.101)
Extension visits in 2016	0.0826**	0.0226	0.00989
	(0.0305)	(0.0161)	(0.0164)
CSA-social network	0.0315	0.00262	0.00336
	(0.0209)	(0.0108)	(0.00919)
Perception of soil fertility	0.758***	-0.0262	0.121
	(0.229)	(0.140)	(0.0714)
Hired labor 1/0	0.749***	0.234*	0.0571
	(0.170)	(0.100)	(0.105)
Cost of hired labor	-0.00000395	-0.00000905	0.0000168
	(0.0000263)	(0.0000120)	(0.0000142)
Amount of fertilizer used (kg)	0.0000354	-0.00127	0.00830*
	(0.00865)	(0.00417)	(0.00409)
Below 2 acres	0.529	0.474**	0.439**
	(0.315)	(0.157)	(0.164)
2–4 acres	0.372	0.0644	0.0549
	(0.253)	(0.125)	(0.145)
Plot on steep slope	-0.350	-0.0561	0.0305
	(0.286)	(0.132)	(0.134)
Credit constrained 1/0	-0.216	0.00106	-0.105
	(0.292)	(0.138)	(0.138)
Livestock owner	-0.0776	-0.183**	-0.0564
	(0.131)	(0.0632)	(0.0608)
Off-farm livelihood sources	-0.293	-0.0720	-0.165
	(0.228)	(0.103)	(0.109)

Table 3.4 cont'd

	Selection equation (Standard error)	**Adopters (Standard error)**	**Non-adopters (Standard error)**
Proportion of WALA beneficiaries	0.0120	0.00341	-0.00233
	(0.00804)	(0.00400)	(0.00381)
House elevation (meters)	-0.000900*	0.000193	0.000132
	(0.000383)	(0.000189)	(0.000213)
Balaka District	0.234	-0.146	0.0631
	(0.372)	(0.178)	(0.182)
Chikwawa District	0.117	-0.342***	-0.00224
	(0.206)	(0.0984)	(0.0916)
Thyolo District	0.294	-0.194	-0.121
	(0.240)	(0.118)	(0.151)
Zomba District	0.811	-0.163	-0.102
	(0.433)	(0.223)	(0.225)
Distance to nearest AEDC office	-0.0478***		
	(0.00749)		
Constant	-3.240***	1.879***	1.854***
	(0.591)	(0.423)	(0.261)
lns1, lns0		-0.582*** (0.0642)	-0.419*** (0.0392)
rho1, rho0		0.8012*** (0.094)	0.5611** (0.199)
Log likelihood	-914.5897		
Wald Chi2	70.79***		
Likelihood ratio test of independent equations Chi 2	12.10***		
Observations		799	

Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: WALA, Wellness and Agriculture for Life Advancement; AEDC, Agricultural Extension Development Coordinator; rho1 & rho0, the correlation between the error term in the selection equation and the structural equation for CSA adopters and non-adopters respectively; lns1, lns0 are the natural logarithms of rho1 and rho0 respectively.

3.4.2 Determinants of yield

We find differences in the effects of the covariates on agricultural yield for adopters and non-adopters, even as certain factors such as previous yields (in this case, yield in 2015), the perception of CSA, and land sizes affect the yields of both regimes almost similarly. These differences indicate that there is heterogeneity between adopters and non-adopters, which justifies the use of a switching regression over ordinary least squares (OLS). The estimated values of the covariance terms (lns1 and lns0) and their correlation coefficients, rho1 and rho0 are both statistically significant (Table 3.4), indicating selection bias for CSA adopters as well as non-adopters. This result is important because it shows that if we fail to account for this selection bias by using, for instance, OLS which does not account for unobserved heterogeneity, model estimates would be biased.

More important, because rho1 (the correlation between the error term in the selection equation and the structural equation for CSA adopters) is statistically significant with a positive sign, it shows that there is a negative selection bias in CSA adoption in this setting. This means that CSA adopters are farmers who have lower-than-average yields in the community. This finding is similar to Kabunga et al. (2012) in Kenya, who found negative selection bias in the causal impacts of banana tissue culture on yields for adopters and non-adopters. Our result is also consistent with Coulibaly et al. (2017) in Malawi, who find negative selection bias in the adoption decisions and outcomes of fertilizer tree adopters as part of agroforestry technology.

In a policy sense, our result indicates that CSA adoption technology is very attractive to farmers with below-average yields in southern Malawi. It is, therefore, a very important finding because it shows the relevance of the WALA watershed development intervention, which was targeted at poor farmers with marginal lands.

3.4.3 Determinants of household income

To estimates the yield income equation, we used a double log function to express the relationship between per capita household income and variables affecting CSA adoption and income. This is a slight modification of the yield determinant model above, which utilizes a lognormal functional form. The double log model proved a better fit based on diagnostic factors such as Pseudo R^2, Log likelihood, and likelihood ratio (LR) tests of model fit. In particular, the double log model had a pseudo R^2 value of 0.8165, a log likelihood of -97.494, and an LR value of 867.53, compared to the lognormal model that had a lower pseudo R^2 value of 0.65803, log likelihood of -222.974, and an LR of 616.57. Table 3.5 shows the determinants of CSA adoption and the impacts on household income. It also shows a considerable level of heterogeneity between the income of adopters and non-adopters in this setting. The lower part of Table 3.5 shows that there is a selection bias in non-adoption of CSA, as indicated by the value of rho0, which is statistically significant. However, unlike Table 3.4, Table 3.5 shows that there is positive selection bias in non-adoption of CSA practices.

Table 3.5: Endogenous switching regression result for determinants of climate-smart agriculture (CSA) adoption and household income

Explanatory variables	Selection equation (Standard error)	Adopters (Standard error)	Non-adopters (Standard error)
Age of household head (years)	0.00518 (0.00490)	-0.00115 (0.00313)	0.00603 (0.00536)
Female-headed household (1 = yes)	-0.0584 (0.139)	-0.0613 (0.0868)	-0.262 (0.148)
Household size	0.0670* (0.0272)	-0.103*** (0.0176)	-0.168*** (0.0292)
Education of household head (years)	0.0654** (0.0231)	-0.0132 (0.0162)	0.01000 (0.0244)
Perception of CSA effects	0.886*** (0.203)	0.125 (0.176)	-0.144 (0.243)

Table 3.5 cont'd

Explanatory variables	**Selection equation (Standard error)**	**Adopters (Standard error)**	**Non-adopters (Standard error)**
Extension visits in 2016	0.109*** (0.0327)	0.00740 (0.0224)	0.0287 (0.0392)
CSA-social network	0.0352 (0.0219)	0.0159 (0.0152)	-0.0505* (0.0228)
Perception of soil fertility	0.701** (0.235)	0.177 (0.205)	0.437* (0.173)
Hired labor 1/0	0.762*** (0.179)	-0.0000748 (0.141)	-0.170 (0.258)
Cost of hired labor	-0.00000966 (0.0000281)	0.0000199 (0.0000165)	0.0000259 (0.0000355)
Amount of fertilizer used (kg)	0.00124 (0.00931)	0.0102 (0.00576)	-0.00671 (0.0101)
Below 2 acres	0.580 (0.329)	0.564** (0.217)	-0.465 (0.409)
2–4 acres	0.397 (0.262)	0.323 (0.173)	-0.159 (0.363)
Plot on steep slope	-0.317 (0.298)	-0.221 (0.183)	0.0709 (0.329)
Credit constrained 1/0	-0.185 (0.311)	-0.358 (0.191)	0.0635 (0.339)
Livestock owner	-0.0142 (0.138)	0.127 (0.0881)	-0.183 (0.151)
Household has additional livelihood sources	-0.259 (0.245)	0.0922 (0.141)	0.0436 (0.271)
Proportion of WALA beneficiaries	0.00953 (0.00849)	0.000706 (0.00559)	-0.00110 (0.00940)
House elevation	-0.000931* (0.000406)	-0.000350 (0.000261)	0.000901 (0.000539)
Balaka District	0.263 (0.370)	0.466 (0.241)	0.745 (0.448)
Chikwawa District	0.0960 (0.215)	0.0879 (0.136)	0.331 (0.228)
Thyolo District	0.438 (0.253)	0.212 (0.161)	-0.480 (0.383)
Zomba District	0.891 (0.457)	0.224 (0.307)	-0.765 (0.565)
Distance to nearest AEDC office	-0.0548*** (0.00835)		

Table 3.5 cont'd

Explanatory variables	**Selection equation (Standard error)**	**Adopters (Standard error)**	**Non-adopters (Standard error)**
Constant	-3.598*** (0.624)	7.092*** (0.587)	6.918*** (0.650)
lns1, lns0		-0.310*** (0.0507)	0.469*** (0.0318)
r1, r2		0.4434** (0.142)	-0.0061 (0.185)
Log likelihood	-1485.107		
Wald Chi2	86.71***		
Likelihood ratio test of independent equations Chi 2	6.18*		
Observations		799	

Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: CSA, climate-smart agriculture; WALA, Wellness and Agriculture for Life Advancement; AEDC, Agricultural Extension Development Coordinator; r1 & r2, the correlation between the error term in the selection equation and the structural equation for CSA adopters and non-adopters respectively; lns1, lns0 are the natural logarithms of rho1 and rho0 respectively.

The result in Table 3.5 implies that farmers with above-average income tend to refrain from CSA adoption, possibly due to the opportunity cost of adoption at least in the short run (Engel & Muller, 2016). This scenario further justifies the need for more information on the relevance of CSA and its longer-term benefits.

3.4.4 Treatment effects: average treatment effects of CSA adoption

In addition to the determinants of CSA adoption on yields and income, the important policy debate for investing in CSA as part of development aid is to estimate the treatment effect of CSA adoption. The important policy question in this setting is what would have been the yield and income of CSA adopters and non-adopters in the absence of CSA adoption? We answer this policy-relevant question of CSA adoption in terms of the counterfactual case (Gertler et al., 2011), showing the average treatment effects of the yields and incomes of adopters and non-adopters of CSA practices (Table 3.6).

Table 3.6: Average treatment effects: Causal impact of climate-smart agriculture (CSA) adoption on yield and income

Outcome	Category of households	CSA-adopting mean	Non-adopting mean	Average treatment effect	Percentage (%)
Maize yield per acre, 2016 (ln)	Adopters	16.609 (0.265)	8.723 (0.113)	7.886*** [0.661]	90.4***
	Non-adopters	7.579 (0.109)	17.060 (0.203)	-9.481 [7.221]	-55.06
Annual maize expenditure per capita (ln)	Adopters	7804.57 (269.98)	5521.41 (168.29)	2283.16*** [668.084]	41.4***
	Non-adopters	4125.16 (151.45)	5914.39 (306.55)	-1789.236 [14510]	-30.25

Significance level: *** $p < 0.01$
Note: analytic standard errors in parentheses; bootstrapped standard errors in brackets at 300 replications; ln implies natural logarithm

The ATT represents the effect of CSA adoption on the yield and income of adopters, while the ATU represents the impact of CSA adoption on the yields and incomes of non-adopters. As shown in equations (8)–(13), the endogenous switching regression estimates the treatment effects of CSA adoption on adopters and non-adopters in a counterfactual framework using a real and hypothetical scenario. To derive valid estimates of the counterfactual case, we estimate the mean outcomes of adopters with and without adoption (i.e., real and hypothetical), and the mean outcomes of non-adopters without and with adoption (i.e., real and hypothetical) using the FIML (Coulibaly et al., 2017; Kabunga et al., 2012; Lokshin & Sajaia, 2004).

In Table 3.6, we interpret the ATTs, which are significant, in terms of natural logarithms (lns) since it would be easier to explain it in terms of elasticity (Noltze et al., 2013). Thus, Table 3.6 shows that the causal impact of CSA adoption on yields per acre is about ln 8 bags (50 kg each). It represents an increase of about 90% in yields, a major change.

Thus, in terms of the counterfactual, CSA adopters may have had 90% less than their 2016 yields had they not adopted the CSA practices. This means that even though the average yields in the study area at the time of the study were relatively low for both adopters and non-adopters due to the drought, adopters would have been much worse if they had not adopted CSA practices. The ATU for yields is not statistically significant in this setting.

The causal impact on the annual per capita household income (for which we use the reported annual expenditure on maize as a proxy) is also positive and statistically significant at the 1% level, with a value of ln MK2283.16. Note that MK represents Malawian Kwacha. The estimated result represents an increase of about 41%, a positive effect of the CSA intervention on household welfare. As with yield, the ATU for household income is not statistically significant. It suggests that current non-adopters may not benefit from CSA adoption, a finding that needs to be interpreted with caution given that CSA is labor intensive and might be cost ineffective in the short term. But as with other environmental management schemes such as payments for ecosystems services, CSA is a public good, which could benefit non-adopters over time (Engel & Muller, 2016).

ROBUSTNESS CHECK

For a robustness check, we estimated yield for 2015, and the effect of CSA adoption on household income for the 2-month period immediately preceding data collection. For the yield in 2015, we simply relied on respondents' recall, as we do not have access to a baseline for 2015. However, since 2015 was a drought year, similar to 2016, we expect that farmers could provide valid responses for their yield in 2015 just as for 2016.

In the 2-month income measure, we followed the Malawi Living Standards Measurement Study questionnaire to ask farm households about their expenditure on maize for the "past two months or 60 days immediately preceding this study." The estimates are in Table 3.7. They show consistency in the ATTs across the two years' outcomes, while the ATU is non-significant. These figures support the robustness of our main results in terms of the yield and income estimates (i.e., Tables 3.4 and 3.5).

Table 3.7: Robustness check for average treatment effects

Outcome	Category of households	CSA-adopting mean	Non-adopting mean	Average treatment effect	Percentage
Ln maize yield per acre, 2015	Adopters	11.838 (0.192)	7.202 (0.143)	4.635 *** [0.583]	64.4***
	Non-adopters	11.197 (0.165)	8.086 (0.163)	3.112 [29.91]	38.5
Ln per capita expenditure for 2 months	Adopters	1096.76 (30.73)	772.21 (29.16)	324.57*** [83.16]	42.03***
	Non-adopters	2012.11 (48.02)	449.92 (20.64)	1562.08 [2050.72]	347.19

Significance level: *** $p < 0.01$
Note: analytic standard errors in parentheses; bootstrapped standard errors in brackets at 300 replications; Ln, natural log; CSA, climate-smart agriculture

Additionally, prior studies (such as Abdulai, 2016; Coulibaly et al., 2017; van Dijk et al., 2017) corroborate the results in this study in terms of the high yields and income impacts from the adoption of climate adaptation and mitigation measures – important components of CSA. For instance, Abdulai, 2016 in Zambia found a 79% increase in agricultural output because of the adoption of conservation agriculture practices – a subset of CSA. Coulibaly et al. (2017) in Malawi found that the adoption of fertilizer trees – agroforestry, which is a component of CSA, has an 82% food security impacts on smallholder farmers with land holdings below 1 care – similar to the present research setting. Similarly, van Dijk et al. (2017) in Tanzania found a maize yield gap of 92%, which they suggested could be narrowed by the promotion of, and application of soil conservation and nutrient improvement practices – components of CSA, among others.

3.5 CONCLUSION

This study has estimated the causal impacts of the adoption of CSA on food security in terms of maize yields (measured in 50 kg bags per acre) and household incomes (measured through per capita household expenditure on maize, the staple crop) in southern Malawi. We used survey data collected in 2016 at a crucial time in the southern region, as the country experienced a severe drought in the 2014/2015 and 2015/2016 growing seasons. Moreover, 2016 marked two years after the end of the large USAID-funded WALA project that included the promotion of soil and water conservation practices through a watershed development intervention designed to build community resilience to climate-change hazards including droughts and floods, which are frequent in southern Malawi.

Although mean yields and consumption expenditures show important differences between adopters and non-adopters of CSA practices, they are insufficient measures of the determinants of CSA adoption decisions (Abdulai & Huffman, 2014). This is because a comparison of means alone does not account for unobserved heterogeneity in the adoption process, and the causal impact of CSA adoption.

Following prior studies (Abdulai, 2016; Jaleta et al., 2018; Noltze et al., 2013; Tesfamariam et al., 2018), we apply an ESR framework, a robust econometric technique that accounts for observed and unobserved heterogeneity. Thus, we controlled for unobserved heterogeneity in CSA adoption decisions as well as the causal impact of adoption in terms of maize yield and household incomes. For maize yields in 2016 as an outcome, the ESR technique identified a negative selection bias in CSA adoption and non-adoption. On the other hand, it identified a positive selection bias in non-adoption decisions regarding per capita household consumption spending of non-adopters in 2016. By accounting for this selection bias, we obtain statistically significant increases of 90.4% and 41.4% in yield and income through consumption spending, respectively, for CSA adopters, whereas, the effects were not statistically significant for non-adopters. The results suggest that CSA adoption has a positive and statistically significant impact on food security through crop yields and household incomes of smallholder farmers in southern Malawi.

This study contributes to the extant literature on climate adaptation aid and CSA by estimating the effects of CSA adoption through an aid-funded CSA intervention, on food security in southern Malawi. It also contributes to development policy in terms of climate adaptation financing for developing countries by highlighting the extent of food security impacts associated with CSA adoption among smallholder farmers in rural settings of direr regions such as southern

Malawi. Policies that enhance CSA adoption among smallholders in vulnerable climate zones are very important for enhancing food security among smallholder farming households in such contexts.

Moreover, the findings of negative selection bias in the structural equation for yield indicates that poorer farm households in southern Malawi would gain the most from CSA adoption. This falls in line with the overarching objective of the WALA project, which was to reduce the food insecurity of poor smallholders in marginal lands. Results suggest that CSA adoption technology is very attractive to farmers with below-average yields in southern Malawi. It is, therefore, a very important finding because it shows the relevance of the WALA watershed development intervention, which was targeted at poor farmers with marginal lands.

This study can be extended into several dimensions to provide better understanding of CSA adoption, and the associated impacts on various outcomes of interest.

Specifically, further research needs emanating from this study include the following: (1). identifying the extent of CSA adoption attributable to specific CSA categories, which would be very helpful in highlighting food security impacts of specific CSA categories in this setting and elsewhere. (2). identifying the mechanisms that underpin CSA adoption, and (3). analyses of biophysical impacts of CSA adoption by CSA category.

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CHAPTER 4:

DOES AGROFORESTRY CONSTITUTE A PATHWAY FOR THE IMPACT OF CLIMATE-SMART AGRICULTURE ON MAIZE YIELDS? A DOUBLE HURDLE APPLICATION FROM SOUTHERN MALAWI[11]

Abstract

Concerns about global food insecurity in the face of climate change have led to increased interest in climate-smart agriculture (CSA), which promises to increase yields while increasing adaptive capacity and mitigating climate change. However, rigorous empirical knowledge of the specific pathways through which CSA interventions may generate greater food security remains minimal. Agroforestry is widely known as a viable land use practice in climate adaptation and mitigation efforts across the globe and may form one such pathway. Here we undertake an empirical analysis of the adoption of agroforestry as a pathway for understanding the effects of CSA interventions on agricultural yields. Using a double hurdle specification with control function and primary survey data from a large-scale CSA intervention in southern Malawi, we estimate the effects of participation in CSA on agricultural yields conditional on agroforestry adoption. We find statistically significant effects of CSA on agricultural yields among agroforestry adopters. The result shows that agroforestry can enhance environmental sustainability and food security. Policies that promote agroforestry adoption in CSA-related intervention have the potential to induce CSA impacts on environmental management and

[11] This chapter is in revision for submission to a journal for publication

increased agricultural yields among smallholder farmers—crucial aspects of sustainable development goals on hunger and climate adaptation.

Keywords: Agroforestry adoption, Double hurdle, agricultural yields, environmental sustainability, southern Malawi.

4.1 INTRODUCTION

Climate change and extreme weather conditions require new adjustments to build resilience and adaptation strategies against destructive environmental shocks such as frequent droughts and floods (IPCC, 2014; Lipper *et al.*, 2014; Adger *et al.*, 2017; Abman, 2018). For instance, the 5th Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) (2014) indicates the need for concerted global efforts to reduce imminent climate-related risks, including droughts and floods affecting global food security and human development challenges, especially for the developing world.

In Sub-Saharan Africa, the effects of climate change through extreme weather events are causing massive food insecurity and humanitarian disasters in the continent (Connolly-Boutin and Smit, 2016; Koren, 2018). One such event is the recent El Niño drought in southern Africa, which seriously affected crop yields in the region for two consecutive farming seasons, 2015 and 2016. The El Niño drought particularly affected maize production in the region by decreasing yields around 12% in 2015 and 26% in 2016 (World Food Programme, 2017; Ubilava, 2018). Malawi and Zimbabwe were the worst hit by the drought, seeing their national maize productions decline by 21% and 42% in 2015 and 2016 for Malawi, and by 37% and 56% in 2015 and 2016 for Zimbabwe, respectively (World Food Programme, 2017).

Such events underscore the need for feasible solutions to climate change and ameliorate its impacts on food and livelihood security in the developing world (World Bank, 2017; World Bank Malawi Office, 2017). Climate-smart agriculture (CSA) is being widely viewed as a solution to the climate change, due to its delivery of three important results: climate adaptation, mitigation, and food security (Lipper *et al.*, 2014; FAO, 2016; Kpadonou *et al.*, 2017; World Food Programme, 2017; Lopez-Ridaura *et al.*, 2018).

Agroforestry, broadly defined as the intentional integration of trees or shrubs with crops or livestock on farms to provide conservation and ecosystem services and socioeconomic benefits (Mbow *et al.*, 2014; Coulibaly *et al.*, 2017; van Noordwijk, 2017), is an example of a prominent CSA practice. It cross-cuts and connects agricultural and environmental fields. For instance, Coulibaly *et al.* (2017, p. 52) consider agroforestry "the interface and interactions between agriculture and forestry, involving farmers, livestock, trees and forests at multiple scales." Therefore, agroforestry is a particularly vital component of CSA and other climate-smart interventions due to its multifaceted benefits of improving crop yields, crop income, and environmental conservation concurrently, through carbon sequestration and nitrogen fixation (Mbow *et al.*, 2014; Coulibaly *et al.*, 2017; Miller *et al.*, 2017).

There is a substantial body of literature on CSA in general (e.g., Lipper *et al.* 2014; Lopez-Ridaura *et al.* 2018; Schaafsma *et al.* 2018) and agroforestry in particular (Miller et al. in review). This literature shows the significance of CSA and agroforestry for environmental management and crop yields among other benefits. However, evidence on the pathways and causal mechanisms through which CSA affects crop yields and other outcomes remains limited.

Analyses of impact pathways and causal mechanisms exist in other domains of natural resource conservation and management (e.g. protected areas Ferraro and Hanauer, 2014, 2015; Newig *et al.*, 2017), but no such analysis exists for CSA impacts. The literature on CSA pathways has focused on adoption and soil conservation for sustainable development (e.g., Scoones, 2015; Nyasimi *et al.*, 2017; Schaafsma *et al.*, 2018), but we are unaware of any study on CSA impact pathways in general, or on agroforestry adoption as a causal mechanism in such studies.

Further, most empirical studies of CSA and agroforestry (e.g., Kuntashula and Mungatana, 2013; Kiptot *et al.*, 2014; Mbow *et al.*, 2014; Coulibaly *et al.*, 2017) focus on direct effects of agroforestry, not as a pathway for how CSA interventions affect crop yields such as maize. Even such studies of impacts are still extremely rare, as a comprehensive recent review shows (Miller et al. in review). Understanding the pathways by which CSA interventions affect crop yields in Sub-Saharan is critical for sustainable development in the face of climate change and its attendant food security and environmental management challenges. Therefore, an important question must be asked: To what extent does agroforestry adoption explain the impact of CSA interventions on agricultural yields?

Here we respond to this question by estimating agroforestry adoption as an impact pathway for CSA interventions on maize yields, taking southern Malawi as a case study. The motivation for this study is the need to provide a basis to understand how agroforestry can link CSA with related outcomes such as agricultural crop yields—an important aspect of overall food security.

Our empirical analysis focuses on a climate-smart intervention funded by the US Agency for International Development (USAID) that was part of a larger project known as Wellness and Agriculture for Life Advancement (WALA), which had a CSA component that promoted eight

CSAs including agroforestry. The aim of the intervention was to tackle persistent environmental degradation and declining soil fertility in the project area and to enhance food security through higher crop yields.

We applied a double hurdle specification with a control function (CF) to test the hypothesis that participants in the CSA program under WALA would realize higher maize yields conditional on agroforestry adoption. Double hurdle models are increasingly popular in empirical analyses of agriculture- and development-related issues that involve sequential outcomes. Examples include agricultural input subsidies and private market participation arising from the subsidy (Ricker-Gilbert *et al.*, 2011; Liverpool-Tasie, 2014; Amankwah *et al.*, 2016), development aid allocation for adaptation to climate change (Weiler *et al.*, 2018), and welfare impacts of improved agricultural technologies (Amare *et al.*, 2012; Verkaart *et al.*, 2017).

This study contributes to the literature by highlighting agroforestry as a pathway for the impacts of CSA on agricultural yields. Additionally, the study extends the frontiers of analyses for prior studies applying the double hurdle model, by our empirical application to an analysis of CSA impacts on yields conditional on agroforestry adoption as an impact pathway.

The rest of the article proceeds as follows: Section 4.2 provides a brief review of the literature and explains the research context; Section 4.3 presents the analytical techniques, including our conceptual framework, empirical strategy, and data; Section 4.4 presents the results and discussion; and Section 4.5 concludes the chapter.

4.2 BACKGROUND INFORMATION

Because CSA and other climate-smart interventions are relatively expensive at scale, many developing-country governments cannot afford the cost of financing climate preparedness (henceforth climate financing). Therefore, the climate justice viewpoint implies a concerted global effort toward climate adaptation and mitigation in the developing world (Adger *et al.*, 2017; Weiler *et al.*, 2018). Thus, there is an increased international action toward climate financing that could climb to US$100 million by the year 2020 (Dinesh *et al.*, 2017; Schaafsma *et al.*, 2018; Weiler *et al.*, 2018). Malawi is an example of countries that have received such climate financing. In the past decade, Malawi has received many climate-related interventions targeted at reducing high environmental degradations and food insecurity, among other efforts (Coulibaly *et al.*, 2017; Dinesh *et al.*, 2017; Ragasa and Mazunda, 2018; Schaafsma *et al.*, 2018).

Despite Malawi's long history of aid, it has had persistent difficulties in the three interrelated spheres of demographic, biophysical, and socioeconomic factors, which has hampered the country's development. Three crucial challenges confronting the country include a high population density of 183 persons per square kilometer (World Bank, 2017), high environmental degradation through deforestation (Mazunda and Shively, 2015; Schaafsma *et al.*, 2018), and associated food insecurity in all rural areas of the country (Coulibaly *et al.*, 2017; Radchenko *et al.*, 2018; Ragasa and Mazunda, 2018). For instance, the national production of maize has been consistently low over the past decade, with an average of 2.1 tons per hectare (Komarek *et al.*, 2017; Radchenko *et al.*, 2018; Ragasa and Mazunda, 2018). The low production rates became worst during the El Niño drought in 2015 and 2016 farming seasons (World Bank Malawi Office, 2017; World Food Programme, 2017; Ubilava, 2018). Moreover, poverty is acute in the country with 71% of the population living below the $1.90/day poverty line (Schaafsma *et al.*, 2018).

In addition to its long-standing food insecurity situation due partly to high environmental degradation such as deforestation and nutrient mining through unsustainable agricultural practices (Coulibaly *et al.*, 2015; Coulibaly *et al.*, 2017; Schaafsma *et al.*, 2018), southern Malawi lags the rest of the country in many developmental outcome indicators. These include a skewness of the national population toward the southern region, accounting for 46% compared to 12% in the northern region (National Statistical Office of Malawi, 2017). Another demographic and socioeconomic problem in the southern region in relation to the rest of Malawi is the disproportionately higher rate of human immunodeficiency virus (HIV) (Zulu *et al.*, 2014). For instance, in a spatiotemporal analysis of the HIV rate in Malawi, Zulu *et al.* (2014) found that by 2010, the average HIV rate in southern Malawi was 4.4% higher than the national average of 10.6%. They also found that Thyolo, Blantyre, and Chiradulu districts, all part of the WALA project, were major hotspots for the virus due to their proximity to a main road and the potential for higher transactional sex.

Against this backdrop, USAID funded a US$86 million integrated food security project under its “Food for Peace” program as a multi-year Title II project in 2009, with the goal of reducing food insecurity across rural communities in eight of the worst-affected districts in southern Malawi. The WALA project spanned the eight districts of Balaka, Chikwawa, Chirazulu, Machinga, Mulanje, Nsanje, Thyolo, and Zomba (Figure 4.1) with several interventions to enhance food security by curbing environmental degradation in the project area.

The eight districts are highly vulnerable to food insecurity through difficult biophysical and socioeconomic conditions such as frequent droughts and high deforestation due to high population density and rural poverty (Reichert, 2014; Verduijn *et al.*, 2014).

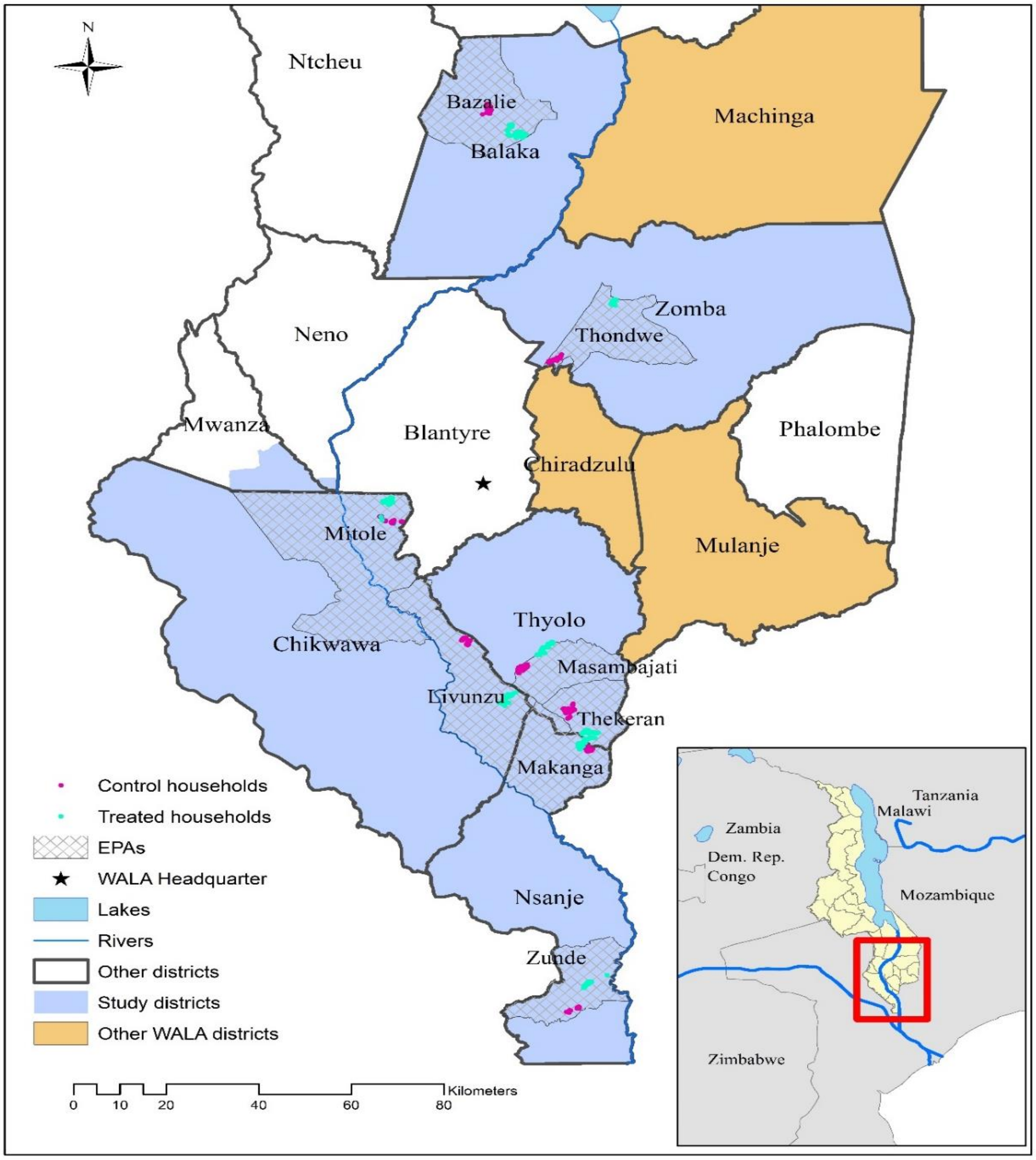

Figure 4.1: Maps of treated and control households within districts.

WALA promoted eight context-specific CSA practices including agroforestry apiculture, check dams, continuous contour trenches (CCTs), marker ridges, stone bunds, vetiver grass, and water absorption trenches (WATs). Households that participated received food for assets (FFA), which included pinto beans and vegetable oil.

The objective of the CSA intervention by WALA was to enhance the adoption of CSA practices by individual farm households in the project area. Thus, the project expected farmers to adopt these practices as a suite of CSA techniques on their agricultural plots (Figure 4.1), thereby achieving food security through higher yields (Reichert, 2014; Verduijn *et al.*, 2014).

WALA's theory of change consisted of reducing food insecurity through the adoption of various CSA practices to minimize soil degradation and improve crop yields, among other efforts. Therefore, the ensuing study focuses on the agroforestry component of the CSA intervention under the WALA project, in relation to agricultural yields.

The study focuses on maize yields because agricultural yields constitute major food security indicators—availability and access—as have been used in many impact assessment studies (e.g., Kabunga *et al.*, 2012; Manda *et al.*, 2016; Steward *et al.*, 2018). Furthermore, because maize is the staple crop in Malawi (Komarek *et al.*, 2017; Radchenko *et al.*, 2018; Ragasa and Mazunda, 2018), its productivity is important and has a significant policy relevance for reducing rural poverty in southern Malawi.

From the extant literature (e.g., Coulibaly *et al.*, 2017; Lipper *et al.*, 2014; van Noordwijk, 2017), we expect agroforestry to improve yields by improving soil fertility and water conservation through prevention of evapotranspiration among others, thereby enhancing increased availability and uptake of critical nutrients such as nitrogen, by crops such as maize. For instance, two important components of agroforestry that significantly contributes to crop yields in relation to this study include (1). Nitrogen fixing trees such as Faidherbia albida, and Albizia lebbeck; and (2). fast-growing shrubs, such as Cajanus cajan, Gliricidia sepium, Leucaena leucocephala, Sesbania sesban, and Tephrosia vogelii (Mbow *et al.*, 2014; Coulibaly *et al.*, 2017). When farmers incorporate these fertilizer trees and shrubs into their farms, they add nitrogen to the soil through nitrification – the process of absorbing nitrogen from the air and adding it to the soil through their root noodles (Coulibaly *et al.*, 2017; van Noordwijk, 2017), and by adding organic matter through leaf littering among others.

4.3 ANALYTICAL FRAMEWORK AND ECONOMETRIC APPROACH

4.3.1 Conceptual framework

We use the theory of the household, which posits that under market imperfection, the production and consumption decisions of smallholder farmers (such as those in our research context of southern Malawi) would be non-separable (Singh *et al.*, 1986; de Janvry and Sadoulet; 2006; D'Souza and Mishra, 2018). The implication is that farmers self-select into program participation or adoption groups, making the impact of development programs heterogeneous. Self-selection in our research context implies that farm households would participate in CSA programs under WALA, with a utility maximization in mindset.

Specifically, we assume that a household maximizes utility ($\overline{U}$) with respect to agricultural production (p_j), consumption function (c_j), and controls (x_j):

$$\overline{U}_J\ (c_j\ , p_j\ , x_j\ ), \tag{4.1}$$

subject to budget constraint and other factors such as biophysical and production technology constraints (Woldeyohanes *et al.*, 2017).

We also note that the level of CSA program impacts on maize yields depends on the probability of adopting agroforestry practices after exposure to CSA treatment. We express this as follows:

$$y_i = \mathrm{f}\left[CSA_p,\ I_j\ ,\ X_j\right], \tag{4.2}$$

where y_i represents maize yield, CSA_p denotes CSA program participation under WALA, I_j and X_j are farm inputs and other covariates including household characteristics (such as age and gender of the household head), institutional factors (such as extension visits), and biophysical factors (such as distance to a treated watershed).

4.3.2 Empirical strategy: Double hurdle specification with a control function

In this study, farmers choose to adopt agroforestry conditional on treatment assignment (i.e., CSA program participation under WALA) and in which the resulting maize yield is conditional on agroforestry. Thus, a non-adoption of agroforestry equally constitutes an optimal choice just as the adoption of agroforestry.

Following several studies in the development literature on natural resources and climate adaptation among others (Noltze *et al.*, 2012; Amankwah *et al.*, 2016; Weiler *et al.*, 2018), we apply a corner solution approach for the extent of maize yield obtainable from participation in the CSA program under WALA, conditional on agroforestry adoption. A corner solution approach handles limited dependent variables consisting of endpoints that could be zeros or ones as an optimal choice (Cragg, 1971; Liverpool-Tasie, 2014; Amankwah *et al.*, 2016).

The Tobit model, developed by Tobin (1958), is a classic corner solution model often suitable in situations where the outcomes (such as yield in this study) simultaneously depend on a prior decision (Amemiya, 1984; Amankwah *et al.*, 2016), such as agroforestry adoption among program participants. In the Tobit model, we interpret the outcome variable conditional on the intermediate decision (such as agroforestry adoption) after the initial selection process.

However, a major weakness of the Tobit model is that it assumes that the partial effects of individual covariates in the adoption decisions and outcome equations have the same sign, whereas, the situation could be different (Noltze *et al.*, 2012; Woldeyohanes *et al.*, 2017; Weiler *et al.*, 2018). For example, although it is possible for a particular variable (such as credit constraint) to influence agroforestry adoption decision, we may not necessarily expect the same variable to influence the resulting yield conditional on a positive adoption. In other words, while credit may be statistically significant for adoption, it may not be statistically significant for yield once the farmer has adopted agroforestry, because other factors may be more important in the determination of yields than credit constraint.

A double hurdle model is particularly suited to the estimation of data that fits within the framework of corner solutions. It is a generalized Tobit model that accounts for sequential decisions in technology adoption processes as well as the resulting outcomes. The double hurdle model relaxes the limitations of the Tobit model by allowing the factors determining the adoption decision to be different from the factors determining the outcome, with extensive empirical applications in the literature involving process and outcomes simultaneously (Woldeyohanes *et al.*, 2017; Adalja and Lichtenberg, 2018; Weiler *et al.*, 2018). Thus, in the context of maize yield owing to agroforestry adoption, the double hurdle model is appropriate for determining the extent of outputs (i.e., maize yield from agroforestry adoption) by separately estimating the factors that determine agroforestry adoption from those that determine the amount obtained from the adoption decision.

Analytically, the double hurdle model in this study uses two probit models—one for the treatment assignment, and another for agroforestry adoption—and a truncated regression for the impact of CSA program participation conditional on the agroforestry adoption decision (i.e., the pathway). Figure 4.2 shows this connection. First, households self-select into the CSA program (as participants), then they cross the first hurdle, which is the decision to adopt agroforestry (1 = yes, 0 otherwise). Consequently, the second hurdle is the associated impact of the program conditional on a positive agroforestry adoption decision.

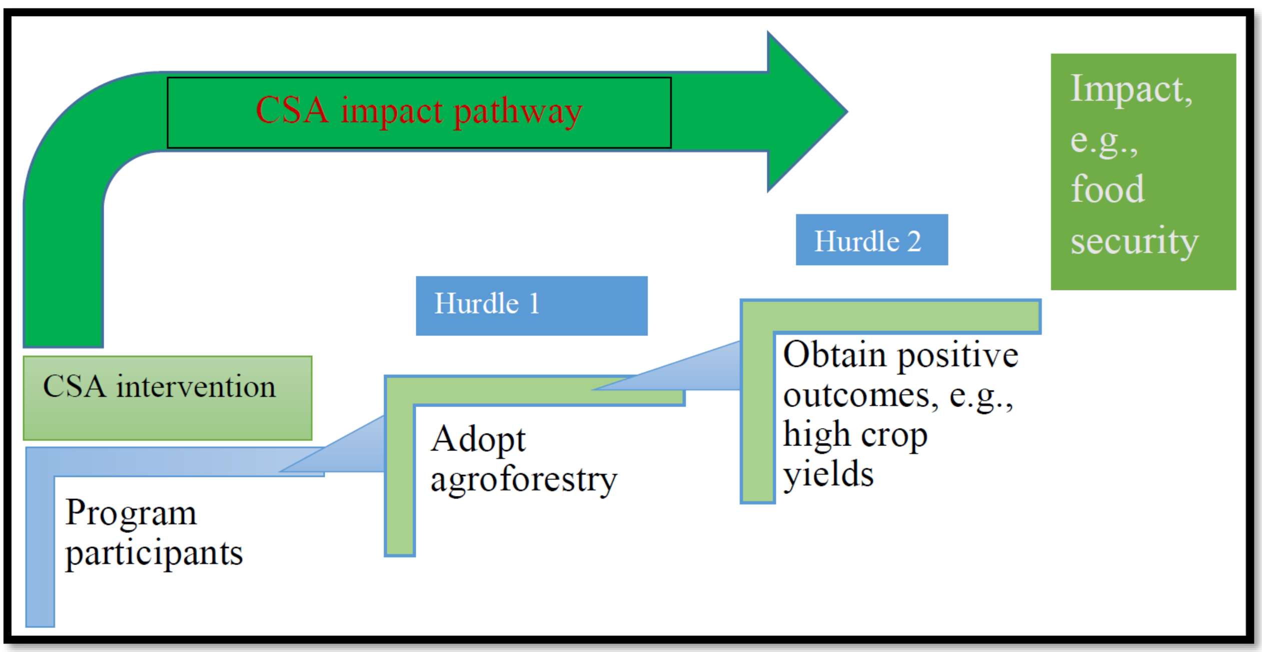

Figure 4.2: Agroforestry adoption as an impact pathway for climate-smart agriculture (CSA) interventions**.**

4.3.2.1 Controlling for unobserved heterogeneity and potential endogeneity in CSA program participation: The control function approach

This study uses a control function (CF) technique to control for potential endogeneity in treatment assignment arising from non-random placement of the CSA program in the study area. CF constitutes a variable or a set of variables whose inclusion in a regression model renders a policy explanatory variable exogenous (Lewbel *et al.*, 2012; Giles *et al.*, 2013; Wooldridge, 2015; Murtazashvili and Wooldridge, 2016). CF solves endogeneity problems in structural equations. Therefore, to account for unobserved heterogeneity in CSA program participation, we use the CF approach as discussed in Wooldridge (2015), with recent empirical applications (Amankwah *et al.*, 2016; Murtazashvili and Wooldridge, 2016; Woldeyohanes *et al.*, 2017).

The CF approach requires several steps. First, we estimate a probability of treatment assignment using a probit model with an instrumental variable (IV) to account for the potential endogeneity of program participation, given that participation was non-random. A valid instrument should be correlated with the treatment variable (program participation) conditional on other variables but uncorrelated with the error terms of the structural equations for Hurdle 1 and Hurdle 2 (i.e., the agroforestry adoption and yield equations, respectively). We then estimate generalized residuals of the participation equation, which we incorporate along with the treatment variable into the first and second hurdles to recover consistent estimates for agroforestry adoption and yield impacts corresponding to Hurdles 1 and 2, respectively (Liverpool-Tasie, 2014; Wooldridge, 2015).

The IV in the CF model is a binary dummy variable that indicates whether the household head had any prior contacts with WALA staff or someone who later became a WALA staff and worked in the community. We regress the CSA participation variable as a function of all explanatory variables of agroforestry adoption and yield equation plus the IV. In the subsequent equations (i.e., second stages) for agroforestry adoption and maize yield, we include the predicted residuals from the first stage participation equation as an additional control along with the participation variable, thereby making that variable exogenous (Wooldridge, 2015; Amankwah *et al.*, 2016; Woldeyohanes *et al.*, 2017; Ragasa and Mazunda, 2018). The CF proceeds as follows:

$$CSA_p = \lambda Ki + \psi X_i + \omega_i \, , \tag{4.3}$$

where CSA_p represents CSA program participation, Ki represents a valid instrument for program participation, which we used to obtain the generalized residual residuals as explained above, and X_i represents observed characteristics.

4.3.2.2 Double hurdle model specification and estimation method

Having controlled for the potential endogeneity of CSA program participation through the CF approach we are now ready to specify the full double hurdle model. Estimating the double hurdle model requires several steps. First, we use another probit model for the probability of agroforestry adoption conditional on program participation and other covariates, including the generalized residual obtained from the CF approach.

Note that we employ probit regression instead of logit regression for the binary variables (i.e., program participation and agroforestry adoption) because the probit model is robust to heteroscedasticity. It is also capable of constraining the outcomes of the CSA program participation and agroforestry adoption within the bounds of zero and one (Mutenje *et al.*, 2016).

Thus, we model the probability of agroforestry adoption as a probit model, applying a random utility framework in which the farmer evaluates the benefits of adopting agroforestry in order to inform his/her decision of whether to adopt agroforestry or not.

Hurdle 1: Agroforestry adoption

$$Agrof_i^* = \pi' Z_i + \xi_i \text{ , with } Agrof_i = \begin{cases} 1, & if\ Agrof^*{}_i > 0, \\ 0, & Otherwise \end{cases} \quad , \tag{4.4}$$

where $Agrof_i^*$ is a latent variable representing the utility of agroforestry adoption, and $Agrof_i$ is the binary dummy for agroforestry adoption. The variable Z_i constitutes a vector of covariates determining agroforestry adoption. These include CSA_p, household characteristics, biophysical factors, institutional factors, and the generalized residuals. π is a vector of parameters to be estimated, while ξ is an error term with zero mean and constant variance.

Hurdle 2: Maize yield conditional on agroforestry adoption and program participation. In the second hurdle, we estimate a truncated regression for maize yield conditional on agroforestry adoption and CSA program participation as follows:

$Yield_i^* = \exp(\beta' \Upsilon_i + \eta_i)$, with observed yield expressed as

$$Yield_i = \begin{cases} Yield^*{}_i, & if\ Yield^*{}_i > 0 \text{ and } Agrof_i = 1, \\ 0, & Otherwise \end{cases} \quad , \tag{4.5}$$

where Υ_i is a vector of yield determinants including CSA program participation, household characteristics, and other controls; β`constitutes a vector of parameters to be estimated; η_i is a log-normal distribution error term with constant variance (σ^2) and a zero mean. We assume that the agroforestry adoption and maize yield equations are independent. We estimate both equations corresponding to Hurdle 1 and Hurdle 2 separately through a maximum likelihood estimation algorithm. However, the interpretation of the yield equation (second hurdle) must always be conditional on the first hurdle (Amankwah *et al.*, 2016; Hitayezu *et al.*, 2017; Woldeyohanes *et al.*, 2017; Weiler *et al.*, 2018). Thus, we maximize the following log-likelihood function for the double hurdle model:

$$\ln(\mathrm{L}) = [1 - \Phi(\pi' Z_i)] + \ln[\Phi(\pi' Z_i)] + \left[\phi\left(\ln(Yield_i) - \frac{\beta' \Upsilon_i}{\sigma}\right) - \ln(\sigma) - ln(Yield_i)\right], \quad (4.6)$$

where $\phi(.)$ and $\Phi(.)$ are, respectively, the normal probability density and cumulative distribution functions. Following Amankwah *et al.* (2016), we can calculate the expected value of maize yield conditional on strictly positive agroforestry adoption as follows:

$$E[Yield_i | \Upsilon_i, \Upsilon > 0] = \exp\left(\beta' \Upsilon_i + \frac{\sigma^2}{2}\right), \quad (4.7)$$

where the parameters are as defined earlier.

Thereafter, we estimate the average partial effects (APEs) of changes in the covariates on the amount of maize yield conditional on agroforestry adoption. Note that the APEs are respectively, evaluated at the maximum likelihood estimates of the dependent variables in the double hurdle model.

4.3.3 Data and variable description

Data for this study came from a sample of 808 households across the farming population in the zone of influence of the WALA project in southern Malawi. We categorize farmers into adopters and non-adopters based on their responses to a survey questionnaire designed specifically for this study. The questionnaire strictly follows the details described above regarding our definition and measure of agroforestry adoption in this setting. Thus, although we collected data from communities that received the agroforestry intervention, and those that did not, we do not expect the spatial boundaries to limit agroforestry adoption.

Data collection began in November 2015 through an intensive scoping exercise and ended in September 2016 following a detailed survey. Data consist of microlevel details of farm households' production and consumption activities during the year 2016 and the preceding 12 months. We also collected community-level data through key informant interviews and personal observations. Additionally, we collected secondary data from the project office in Blantyre and Agricultural Extension Officers across the respective districts.

We use a multistage proportional sampling framework to select 16 grouped village headman (GVHs) communities from eight Extension Planning Areas (EPAs) across five of eight WALA districts that we selected for this analysis. The multistage sampling and data collection framework were as follows: First, we selected two EPAs per district, depending on the locations of watershed development sites and the spatial distribution of villages around the watershed. For example, we ensured a distance of about 20–25 km between treatment and control GVHs in order to ensure that randomly selected households in the control area did not easily get the WALA treatment, if ever. Second, we selected two GVH per EPA, making the total number per district equal to four. Each GVH had households that were participants in the WALA intervention, or not, but not both. In each GVH, we selected 15% of the households based on community records. In the end, we collected household survey data from 808 households selected proportional to the size of their GVHs,

All enumerators were Malawians fluent in the main local language (Chichewa). They all received training on administering the questionnaires for this study. Training also included a day of pretesting and several days of feedback loops prior to the actual survey. During the survey, we closely supervised all enumerators to ensure data quality and other important standards. We used a list of households per GVH, which we had obtained from WALA project staff and community natural resources management groups in the study area to select households for the analyses. We collected household-, plot-, and community-level data such as distance to extension offices and main roads.

4.3.3.1 Measures of program participation, agroforestry adoption, and maize yields

In this study, we define program participation as a measure of three factors that households must meet to be included as participants. First, a household must have resided in the community prior to the CSA intervention by WALA. Second, the household must have been actively involved in a natural resource management group (such as a watershed development committee) prior to the intervention. Third, the household must have actively participated in the CSA training program that WALA promoted at the community level, by having at least one person from the household participate in the watershed development work at their community level. Moreover, it is possible that this third factor is slightly lax because some households in non-WALA communities were able to slip through community boundaries to receive the FFA.

Our measure of agroforestry adoption is farmers' self-reported record of adoption as part of the WALA project for at least the four years from 2012 (during the mid-term review of WALA) to 2016, the time of data collection for this study. This adoption measure is similar to two closely related studies in Malawi. First, Coulibaly *et al.* (2017) used five years of farmers' reported cultivation of agroforestry, and Mutenje *et al.* (2016) use three years of reported implementation of CSA practices. A drawback of this definition is the issue of not having observed farmers' adoption status for the entire period, as noted in Coulibaly *et al.* (2017). To correct this problem, we use administrative data from the WALA project and Ministry of Agriculture in the respective districts to corroborate farmers' claims of the time they started implementing agroforestry on their farms under the WALA project. We also used a list of farmers' groups in the project area to identify farmers who had been in the WALA program and actually started implementing agroforestry in as early as 2010.

Second, we collected plot-level data from each of the farm households in the study area wherein we visually inspected the existence of trees (or lack thereof) on farms and by further probing the household head on the approximate age of the oldest agroforestry tree(s) on the farm.

Before visiting each farm, we asked the household heads or their representatives to show us their main agricultural plot with at least one agroforestry tree that they had planted as a soil and water conservation measure since 2009. This helped us avoid further complications in measuring households reported versus actual practices.

Yields are self-reported amounts of maize harvested in the 2016-farming season, measured in 50kg bags. We divide this by the size of the maize plot for 2016 and report it here as yield per acre (land sizes are in acres in this setting).

4.3.3.2 Description of variables (covariates) and their a priori expectations

Table 4.1 describes the main variables in this study and their a priori expectations. There are two dependent variables: agroforestry adoption and maize yield per acre, both of which we described in Section 4.3.3.1. The main policy variable of interest is CSA program participation. To test the robustness of this variable, we propose a potentially rival policy variable, community labor for FFA. We conjecture that our main policy variable (CSA program participation) should better explain the causal impact of agroforestry adoption and maize yield by having a stronger level of significance in both direction and magnitude, than the rival policy variable (Ferraro and Hanauer, 2014; Ferraro and Hanauer, 2015; Newig *et al.*, 2017).

Table 4.1: Hypotheses and a priori expectation for main variables

Variable	Description	A priori expectation for participation and adoption	Indicative reference
Dependent variable			
Agroforestry adoption	Dummy variable 1/0 for whether a household adopts agroforestry	Positive (+) (due to CSA program intervention)	
Maize yield per acre	Amount of maize yield in 2016	+ (via agroforestry adoption under the CSA program)	
Treatment variable			
CSA program participation	Dummy = 1 if the household resides in a WALA community and participated in CSA program under WALA	+; indicates treatment probability	
Community labor for FFA	A dummy variable = 1 if the household provided labor at the community-level watershed development for FFA. It provides a robustness check for our main treatment variable	Ambiguous	
CSA categories that WALA promoted			
Non-woody plants	Adoption of non-woody plants such as vetiver grass	+	Ma *et al.* (2017)
Assisted natural regeneration	Participation in apiculture for the adoption of CSA	+	Ma *et al.* (2017)
Physical infrastructure	Adoption of physical infrastructures such as stone bunds and continuous contour trenches	+	Abdulai and Huffman (2014)
Other CSA categories			
Residue addition			
Mix measures			
Household characteristics			
Age	Reported age of the household head (years)	+	Coulibaly *et al.* (2017)
Female-headed household (1 = yes)	A dummy for whether the household head is a female	Ambiguous	
Education	Number of years the household head spent in school (years)	+	Coulibaly *et al.* (2017)

Table 4.1 cont'd

Variable	Description	A priori expectation for participation and adoption	Indicative reference
Household size	The reported number of people per household	Ambiguous but expected to be + here	Abdulai and Huffman (2014)
Group membership	Dummy = 1 if the household head belonged to a farmers' group before WALA	+; indicates social capital	
Kinship network	Number of close relatives the household counts on for support in and outside the village	Ambiguous but expected to be + here	Di Falco and Bulte (2013)
Off-farm income	Dummy for whether the household has non-farm livelihood sources (1 = yes, 0 otherwise)	Ambiguous; depends on the outcome	Woldeyohanes *et al.* (2017)
Land ownership (1/0)	Dummy for whether the household head owns land (1 = yes; 0, otherwise)	+; indication of capital	Herrmann (2017)
Total land size	The size of land available to the household, measured in acres	+; indication of capital	
Number of plots	The total number of plots cultivated by the household, including the main plots for maize	+; an indicator of access to capital	
Hired labor	Dummy for hired labor	Positive effect	Abdulai (2016)
Livestock ownership (1/0)	Dummy for whether the household has livestock (1 = yes, 0 otherwise)	Ambiguous depending on the outcome types	Woldeyohanes *et al.* (2017)
Fertilizer application	Dummy for application of fertilizer in 2016 (1 = yes, 0 otherwise)	+; indication of capital	
Institutional factors			
Extension visit	Approximate number of contacts with all extension agents in 2016	+; since it indicated access to information	Ma *et al.* (2017); Abdulai (2016)
Credit constraint	A dummy = 1 if the household feels credit was constrained in 2015/2016 cropping season	-ve	Abdulai (2016)
Food aid	A dummy = 1 if the household received drought-related food aid in 2015/16.	-ve; indicated climate shock	
CSA information sources	Number of CSA-related information sources available to the household	+; indicated access to information	

Table 4.1 cont'd

Variable	Description	A priori expectation for participation and adoption	Indicative reference
NGO extension	Dummy for whether the household received extension information from any NGO in 2015/16 (1 = yes, 0 otherwise).	+; indicated access to information	
Biophysical factors			
House elevation	House elevation in meters	Ambiguous	-
Plot is steep	A dummy = 1 if the maize plot is steep	+	
Distance to a treated watershed	Distance in kilometers to the treated watershed in the community or neighboring area	-ve for participation, neutral for adoption	
Perception of soil fertility	Dummy = 1 if the household considers the maize plot as fertile or not	+	
Districts			
Balaka	Dummy for household residing in Balaka District (1 = yes, 0 otherwise)	Ambiguous	Coulibaly *et al.* (2015)
Chikwawa	Dummy for household residing in Chikwawa District (yes = 1, 0 otherwise)	Ambiguous	Coulibaly *et al.* (2015)
Nsanje	Dummy for household residing in Nsanje District (1 = yes, 0 otherwise)	Ambiguous	Coulibaly *et al.* (2015)
Thyolo	Dummy for household residing in Thyolo District (1 = yes, 0 otherwise)	Ambiguous	Coulibaly *et al.* (2015)
Zomba	Dummy for household residing in Zomba District (1 = yes, 0 otherwise)	Ambiguous	Coulibaly *et al.* (2015)
Instrumental variable			
Prior contact	A dummy variable for whether the household had any prior contacts with WALA staff	+; indicates treatment probability	

Note: CSA, climate-smart agriculture; FFA, food for assets; WALA, Wellness, and Agriculture for Life Advancement; NGO, non-government organization

4.3.4 Descriptive and summary statistics

Table 4.2 shows the descriptive statistics for the main variables for this study. It shows significant levels of heterogeneity between the treatment and control groups. For instance, maize yield and agroforestry adoption rates in the treatment population are statistically different from those in the control group. In terms of demographic characteristics, the treatment group has more males than females, as opposed to the control group, which has more females in the sample.

In terms of resource endowment, participants have more social capital than the control group in terms of group memberships and kinship network. Similarly, participants have more plots, labor endowment, livestock ownership, fertilizer application rates, and extension visits, and fewer credit constraints than the control group.

Biophysical factors are also different, with participants having steeper plots and more fertile soils than the control group, and their farms are closer to a treated watershed compared to the control group. Similarly, there are statistically significant differences between program participants and non-participants in terms of their adoption of all CSA categories including non-woody plants (such as vetiver grass), physical infrastructures (such as stone bunds), assisted regeneration, residue addition, and mixed measures. These differences imply that program participants and non-participants are systematically different, which leads the application of ordinary least squares (OLS) regression techniques as an estimation of the impact of WALA to produce bias and inconsistent estimates. Matching estimators, such as propensity score matching (PSM), would also produce bias estimates because they do not control for unobserved differences between participants and non-participants in the research setting. Therefore, we instead applied the double hurdle model with a control function as a more rigorous method for estimating the true impact of the CSA program participation in terms of maize yields.

Table 4.2: Summary statistics

Variables	Treatment group (n = 450)		Control (n = 358)		Difference (N = 808)
	Mean	**SD**	**Mean**	**SD**	**Mean**
Maize yield (50 kg bags)	7.973	5.734	4.596	4.353	3.377***
Agroforestry adoption (%)	0.602	0.493	0.173	0.379	0.429***
Community labor participation	0.842	0.500	0.128	0.335	0.714***
Age	43.607	15.554	41.852	15.877	1.755
Female-headed household	0.416	0.499	0.536	0.499	-0.121***
Education level (years)	4.647	1.910	4.559	1.965	0.088
Household size	6.318	2.317	6.570	2.287	-0.252
Prior group membership	0.856	0.480	0.374	0.485	0.481***
Kinship network	3.780	2.117	0.849	1.246	2.931***
Off-farm income	0.613	0.491	0.570	0.496	0.044
Total land size	0.211	0.399	0.182	0.386	0.030
Total number of plots	2.758	0.947	2.448	0.900	0.310***
Plot size of other main crops	1.833	0.859	1.885	0.873	-0.052
Hired labor	0.769	0.500	0.101	0.301	0.668***
Livestock ownership	0.499	0.499	0.427	0.495	0.072**
Fertilizer application	0.816	0.496	0.246	0.431	0.570***
Extension visits	9.051	3.183	5.061	2.313	3.990***
Regular extension visits	0.544	0.499	0.520	0.500	0.025
Credit constrained	0.364	0.494	0.492	0.501	-0.127***
CSA information sources	4.956	0.861	4.939	0.783	0.017
NGO extension	7.591	1.860	5.927	1.650	1.664***
Plot is steep	0.533	0.500	0.433	0.496	0.100***
Perception of soil fertility	0.882	0.475	0.377	0.485	0.505***
Plot distance from the homestead	1.116	3.471	1.457	4.934	-0.340
Distance to an untreated watershed	8.539	8.667	3.973	6.837	4.566***
Distance to a treated watershed	2.690	10.099	15.532	11.121	-12.841***
Non-woody plants	0.422	0.447	0.092	0.290	0.330***
Assisted regeneration	0.504	0.482	0.196	0.397	0.309***
Physical Infrastructure	0.940	0.463	0.374	0.485	0.566***
Residue addition	0.560	0.492	0.218	0.413	0.342***
Mix measures	0.867	0.315	0.916	0.277	-0.050**
Balaka District	0.136	0.315	0.081	0.273	0.055**
Chikwawa District	0.293	0.450	0.265	0.442	0.028
Nsanje District	0.191	0.400	0.209	0.408	-0.018
Thyolo District	0.284	0.464	0.349	0.477	-0.065**
Zomba District	0.096	0.294	0.095	0.294	0.001

Significance levels: * < 10%; ** < 5%; *** < 1%

Note: CSA, climate-smart agriculture; NGO, non-government organization

Source: Authors' calculation using Stata 15MP

Because WALA promoted agroforestry along with other CSA categories, including non-woody plants, assisted regeneration, and physical infrastructure (Amadu *et al.*, 2018), we have to control for them along with other CSA categories that WALA did not specifically promote.

We also show (Figure 4.3) the adoption rates in our sample across districts. Figure 4.3 shows that Chikwawa district has the highest proportion of agroforestry adoption, accounting for about 31%, followed by Thyolo and Nsanje districts with 25% and 19%, respectively. Zomba and Balaka districts have the lowest agroforestry adoption rates, accounting for 11% and 14%, respectively.

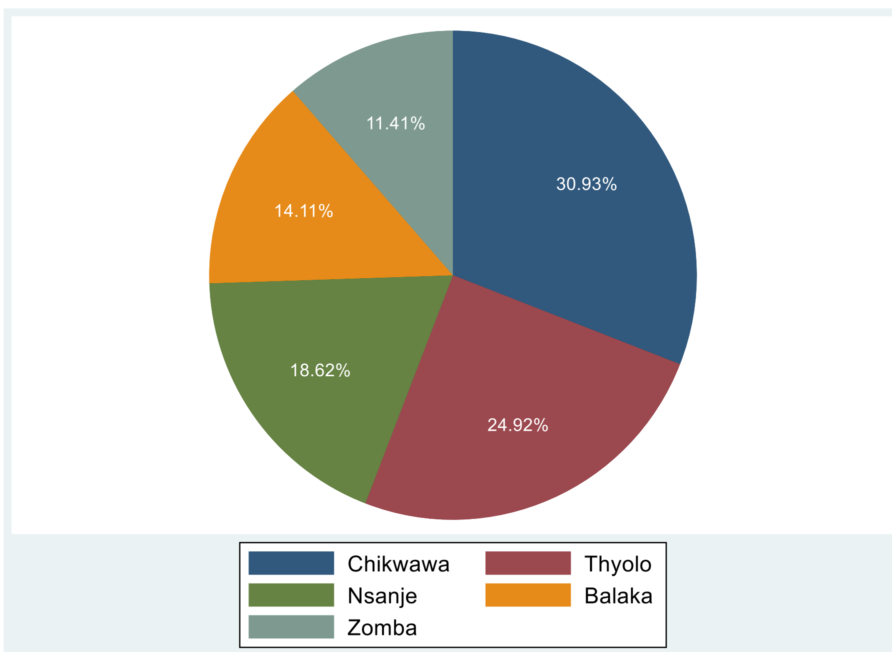

Figure 4.3: Percentage of agroforestry adoption by district.

4.4 RESULTS AND DISCUSSION

4.4.1 Determinants of participation in CSA program under WALA

Before showing results from the main estimates of the double hurdle specifications, we will discuss the result of the first-stage estimation for the determinants of CSA program participation and the rival policy variable, community labor for FFA. Table 4.3. Note that determinants of treatment assignment are not the focus of this study. Therefore, we will not concentrate on these results.

However, the main goal of Table 4.3 is to show the validity of the proposed instrument variable (i.e., prior contact) used in the CF model for CSA participation and the rival policy variable as explained in Section 4.3.2. Table 4.3 shows that the instrument is highly significant in the selection equations corresponding to both the policy variable and the community labor for FFA variable.

Table 4.3: First-stage regressions results of the determinants of program participation

Explanatory variable (covariates)	**Participation in CSA**		**Community labor for FFA**	
	Coefficient	**p-value**	**Coefficient**	**p-value**
Age	0.001	0.910	0.002	0.567
Female-headed household	-0.542*	0.007	-0.450***	0.001
Education level (years)	-0.021	0.640	-0.040	0.221
Household size	-0.036	0.376	-0.006	0.834
Prior group membership	0.747***	0.000	0.750***	0.000
Kinship network	0.174**	0.003	0.231***	0.000
Off-farm income	0.131	0.583	0.338*	0.036
Total land size	0.111	0.373	-0.073	0.353
Total number of plots	-0.100	0.330	-0.015	0.833
Plot size of other main crops	-0.136	0.324	-0.108	0.228
Hired labor	0.890***	0.000	0.538***	0.001
Livestock ownership	0.080	0.666	-0.090	0.473
Fertilizer application	0.556*	0.009	0.260	0.088
Extension visits	0.232***	0.000	0.084***	0.001

Table 4.3 cont'd

Explanatory variable (covariates)	Participation in CSA		Community labor for FFA	
	Coefficient	p-value	Coefficient	p-value
Credit constrained	-0.419	0.259	-0.620*	0.016
Plot is steep	-0.070	0.839	-0.547*	0.023
Perception of soil fertility	0.189	0.367	0.175	0.246
Plot distance from the homestead	-0.063	0.336	0.009	0.604
Distance to an untreated watershed	0.049**	0.003	0.017*	0.035
Distance to a treated watershed	-0.078***	0.000	-0.018*	0.014
Balaka District	-0.420	0.275	-0.412	0.109
Nsanje District	-0.266	0.357	0.226	0.224
Thyolo District	-0.565*	0.037	-0.050	0.769
Zomba District	-0.612	0.082	-0.010	0.968
Prior contacts	0.602**	0.004	0.559***	0.000
Constant	-1.861*	0.012	-1.077*	0.024
Number of observation	807.000		807.000	
Log-likelihood	-127.848		-278.146	
Likelihood ratio Chi2	852.760***	0.000	560.360***	0.000
Pseudo-R2	0.769		0.502	

Significance levels: *10%; **5%; ***1%
Note: CSA, climate-smart agriculture; FFA, food for assets
Source: Authors' calculation using Stata 15MP

This variable does not have a statistically significant correlation with any of the outcome equations (Table 4.4). Accordingly, the instrument is valid in this context.

Table 4.4: Correlation of outcome variables with the instrumental variable (IV) used

Outcome variable	Correlation with IV	P-value
Agroforestry adoption	-.040	.256
Maize per acre	-.004	.916
Log of maize yield per acre	.023	.524

4.4.2 Determinants of agroforestry adoption and the extent of maize yield

Table 4.5 shows the average partial effects (APEs) of the determinants of agroforestry adoption and maize yield conditional on agroforestry adoption. As noted in Section 4.3.3, the generalized residuals from the reduced-form participation equation are included as covariates in the structural equations for Hurdle 1 and Hurdle 2 (i.e., agroforestry adoption and maize yield respectively). The estimated coefficient for the participation residual (i.e., the generalized residual) is not statistically significant across all models. This suggests that in each specification, the treatment variable has been consistently estimated (Wooldridge, 2015; Ma *et al.*, 2017; Tesfamariam *et al.*, 2018). Note that we transformed the continuous variable (yield per acre) into a natural logarithm to be interpretable in terms of percentage.

Socioeconomic factors that determine agroforestry adoption include the age of the household head and off-farm income. Age is significant at 10%, albeit with a low magnitude. Age symbolizes experience, and is thus expected to influence agroforestry adoption decisions, as in Asfaw *et al.* (2016) and Miller *et al.* (2017), for example, but has been statistically non-significant in others (e.g., Coulibaly *et al.*, 2017; Kpadonou *et al.*, 2017; D'Souza and Mishra, 2018). Once a household decides to adopt agroforestry, age is no longer a significant factor in the extent of yield conditional on adoption.

Kinship networks are not statistically significant in the adoption decision, but they are significant in the yield equation at 10% level of significance. The APE suggests that each additional kinship connection a household establishes increases the likelihood of obtaining higher yields by 3.4%. This implies that kinships are vital in the rural economy of southern Malawi. In the literature, the effects of kinships are ambiguous depending on their types. Specifically, our result is consistent with earlier results by Abdulai (2016), Kpadonou *et al.* (2017), and D'Souza and Mishra (2018) for kinships that constitute social networks, but contrasts with the findings of Di Falco and Bulte (2013) in Ethiopia.

Another statistically significant socioeconomic factor influencing agroforestry adoption is off-farm income, which is significant at 5%, indicating that off-farm income increases the probability of agroforestry adoption by 11.4% in this setting. This result is consistent with Noltze *et al.* (2012) and Coulibaly *et al.* (2017) but contrary to Verkaart *et al.* (2017) and Woldeyohanes *et al.* (2017). As with the age of the household head, off-farm income ceases to influence yield after the decision to adopt agroforestry. This is probably because the adoption process is more resource intensive than the management of the farm after adoption.

Resource endowment including total land size, plot size allocated to other crops, and hired labor are statistically significant in the yield equation. The result shows that conditional on agroforestry adoption, every additional acre of land available to the household increases maize yield by 14 %. On the contrary, every additional acre of land allocated to other crops will reduce the extent of maize yield by 41%. In this setting, most households have more than one plot including the main plot, which is often the plot with maize and a subsidiary crop such as rice, cowpea, or pigeon pea. This result implies that multiple cultivating crops can reduce the number of resources devoted to maize cultivation, and thus negatively affects maize production. Hired labor has the expected sign, which suggests that conditional on agroforestry adoption, every additional person employed on the maize farm increases annual maize yields by 18% on average.

Furthermore, Table 4.5 shows that biophysical factors, including soil fertility, distance to a treated watershed, and the adoption of other CSA categories such as non-woody plants, residue addition, and mixed measures, will affect the adoption of agroforestry in this context. For instance, adoption of non-woody plants will increase the likelihood of adopting agroforestry by 14.8 %. On the other hand, the adoption of residues and mixed measures will decrease the chance of adopting agroforestry by 7.1% and 32%, respectively.

In Table 4.5, the main explanatory variable of interest is the CSA participation, which is the treatment (i.e., policy variable) in this study. Table 4.5 shows that the APE for program participation is positive and statistically significant at 1% in both structural equations for agroforestry adoption and maize yield. It shows that holding other factors constant, CSA program participation increases the probability of agroforestry adoption by 28.7 %. Likewise, the result implies that CSA participants who adopt agroforestry will realize maize yield increases of by 31.2 %. This result has vital food and environmental policy implications in that it suggests that making agroforestry adoption a centerpiece of CSA interventions could significantly increase food security through increased yields among smallholder farmers in southern Malawi with potential relevance in other dryland developing country contexts.

Additionally, diagnostic tests show that the model fits the data very well. The Wald chi-squared (χ^2) tests statistics are 202.140 (p-value = 0.000) and 556.500 (p-value = 0.000) for Hurdle 1 and Hurdle 2, respectively. Thus, these statistically significant results suggest that we can reject the null hypothesis that both hurdles (i.e., agroforestry and yield equation) are not jointly determined, favoring the application of the double hurdle model instead.

Table 4.5: Main result of double hurdle estimates of the effect of climate-smart agriculture (CSA) participation on maize yield conditional on agroforestry adoption

	Hurdle 1: Adoption of agroforestry		**Hurdle 2: Log of maize yield, 2016**	
Variables	**APE**	**P > |z|**	**APE**	**P > |z|**
Watershed development	0.287***	0.000	0.312***	0.001
Age	0.002*	0.050	-0.001	0.664
Female-headed household	-0.049	0.108	0.017	0.687
Education level (years)	0.007	0.402	0.019	0.112
Household size	0.000	0.968	-0.010	0.284
Prior group membership	0.007	0.859	0.020	0.694
Kinship network	-0.011	0.335	0.034*	0.033
Off-farm income	0.114**	0.003	-0.014	0.802
Total land size	0.034	0.065	0.142***	0.000

Table 4.5 cont'd

Variables	Hurdle 1: Adoption of agroforestry		Hurdle 2: Log of maize yield, 2016	
	APE	**P > |z|**	**APE**	**P > |z|**
Total number of plots	-0.005	0.801	0.009	0.696
Plot size of other main crops	-0.027	0.203	-0.411***	0.000
Hired labor	0.035	0.423	0.179**	0.002
Livestock ownership	-0.027	0.369	0.007	0.869
Fertilizer application	-0.052	0.212	0.011	0.830
Extension visits	-0.013	0.675	-0.050	0.249
Credit constrained	-0.032	0.658	-0.143	0.129
Plot is steep	-0.084	0.217	-0.030	0.738
Perception of soil fertility	-0.012	0.781	0.246***	0.000
Plot distance from the homestead	-0.003	0.470	0.003	0.268
Distance to an untreated watershed	-0.001	0.481	-0.002	0.474
Distance to a treated watershed	-0.004	0.059	0.008**	0.005
Non-woody plants	0.148***	0.000	-0.056	0.284
Assisted regeneration	0.019	0.556	-0.014	0.746
Physical infrastructure	0.065	0.147	-0.216***	0.001
Residue addition	-0.071*	0.045	0.102*	0.028
Mix measures	-0.318***	0.000	0.180*	0.009
Balaka District	0.002	0.976	-0.043	0.641
Nsanje District	0.069	0.145	-0.501***	0.000
Thyolo District	0.040	0.406	-0.117	0.052
Zomba District	0.102	0.068	0.195*	0.009
Generalized residual	0.007	0.948	-0.115	0.465
Number of observation	807.000		770.000	
Log-pseudo likelihood	-419.641		-640.837	
Wald Chi2	202.140***	0.000	556.500***	0.000
Pseudo-R2	0.232			
Sigma			0.557***	0.000

Significance levels: * < 10%; ** < 5%; *** < 1%
Note: Chikwawa District is the base category.
Source: Authors' calculation using Stata 15MP

4.4.3 Robustness checks

To test the robustness of our main estimates in Table 4.5, we run two other specifications of the double hurdle models. First, we incorporate two additional covariates: One dummy variable equals 1 if the household received any CSA-related information from any non-government organization (NGO) in the form of extension services or natural resources management in the last two years following WALA (2015–2016). The second additional control variable asks about the number of CSA information sources available to the household in the past two years. If these two variables are significant, they would reduce the effect of the main estimate. The result, as shown in Table 4.6, shows that the inclusion of these two covariates does not affect our main estimate. Moreover, both of these extra covariates are not statistically significant, which implies that the model does not suffer from omitted variable bias.

Our next robustness check uses the variable community labor for FFA in place of CSA program participation in the treatment. As explained earlier, if this variable is statistically significant, it may question the validity of the original treatment, as it may suggest that WALA's selection criteria were weak. Table 4.6 shows that this variable is not statistically significant across both hurdles. Thus, it suggests that program participation is the main causal mechanism generating the effect on maize yield through agroforestry adoption as the pathway.

Table 4.6: Robustness check of double hurdle estimate of the effect of climate-smart agriculture (CSA) participation on maize yield conditional on agroforestry adoption

	Hurdle 1: Adoption of agroforestry		**Hurdle 2: Log of maize yield, 2016**	
Variables	**APE**	**P > |z|**	**APE**	**P > |z|**
Watershed development	0.292***	0.000	0.312***	0.001
Age	0.002*	0.050	-0.001	0.673
Female-headed household	-0.050	0.101	0.018	0.679
Education level (years)	0.007	0.398	0.019	0.113
Household size	0.000	0.969	-0.010	0.276
Prior group membership	0.009	0.811	0.019	0.709
Kinship network	-0.011	0.319	0.034*	0.032
Off-farm income	0.114**	0.003	-0.015	0.792
Total land size	0.034	0.064	0.142***	0.000
Total number of plots	-0.005	0.779	0.009	0.695
Plot size of other main crops	-0.029	0.170	-0.410***	0.000
Hired labor	0.036	0.410	0.180**	0.002
Livestock ownership	-0.025	0.404	0.006	0.880
Fertilizer application	-0.051	0.219	0.011	0.826

Table 4.6 cont'd

	Hurdle 1: Adoption of agroforestry		Hurdle 2: Log of maize yield, 2016	
Variables	**APE**	**P > |z|**	**APE**	**P > |z|**
Extension visits	-0.014	0.666	-0.049	0.251
Credit constrained	-0.036	0.621	-0.141	0.137
CSA information sources	0.019	0.237	-0.011	0.660
NGO extension	-0.003	0.772	-0.001	0.949
Plot is steep	-0.085	0.211	-0.029	0.748
Perception of soil fertility	-0.012	0.776	0.246***	0.000
Plot distance from the homestead	-0.003	0.474	0.003	0.266
Distance to an untreated watershed	-0.001	0.454	-0.002	0.474
Distance to a treated watershed	-0.004	0.066	0.008*	0.006
Non-woody plants	0.146***	0.000	-0.055	0.290
Assisted regeneration	0.019	0.563	-0.013	0.754
Physical infrastructure	0.065	0.143	-0.216***	0.001
Residue addition	-0.070*	0.047	0.102*	0.028
Mix measures	-0.312***	0.000	0.178*	0.010
Balaka District	0.001	0.994	-0.040	0.663
Nsanje District	0.066	0.158	-0.500***	0.000
Thyolo District	0.044	0.350	-0.118	0.057
Zomba District	0.107	0.058	0.194*	0.010
Generalized residual	-0.007	0.949	-0.108	0.497
Number of observation	807.000			
Log-pseudo likelihood	-419.042		-640.730	
Wald Chi2	204.660***	0.000	555.590***	0.000
Pseudo-R2	0.233			
Sigma			0.557***	0.000

Significance levels: * < 10%; ** < 5%; *** < 1%
Note: Chikwawa District is the base category; NGO, non-government organization
Source: Authors' calculation using Stata 15MP

Table 4.7: Robustness check of Double Hurdle estimate of the effect of participation in community labor for food for assets (FFA) on maize yield conditional on agroforestry adoption

	Hurdle 1: Adoption of agroforestry		Hurdle 2: Log of maize yield, 2016	
Variables	**APE**	**P > |z|**	**APE**	**P > |z|**
Community labor for FFA	-0.024	0.589	0.112	0.057
Age	0.002*	0.046	-0.001	0.697
Female-headed household	-0.061*	0.048	0.011	0.809
Education level (years)	0.007	0.362	0.020	0.083
Household size	-0.003	0.673	-0.012	0.174
Prior group membership	0.056	0.133	0.040	0.440

Table 4.7 cont'd

	Hurdle 1: Adoption of agroforestry		Hurdle 2: Log of maize yield, 2016	
Variables	**APE**	**P > |z|**	**APE**	**P > |z|**
Kinship network	0.005	0.623	0.042**	0.005
Off-farm income	0.126***	0.001	-0.013	0.829
Total land size	0.038*	0.044	0.147***	0.000
Total number of plots	-0.006	0.749	0.008	0.718
Plot size of other main crops	-0.032	0.135	-0.414***	0.000
Hired labor	0.093*	0.031	0.217***	0.000
Livestock ownership	-0.021	0.496	0.012	0.772
Fertilizer application	-0.027	0.511	0.025	0.632
Extension visits	-0.010	0.745	-0.047	0.281
Credit constrained	-0.029	0.694	-0.121	0.200
Plot is steep	-0.080	0.263	-0.006	0.949
Perception of soil fertility	0.005	0.903	0.258***	0.000
Plot distance from the homestead	-0.003	0.422	0.002	0.391
Distance to an untreated watershed	-0.001	0.757	-0.001	0.614
Distance to a treated watershed	-0.008***	0.000	0.005	0.070
Non-woody plants	0.175***	0.000	-0.028	0.586
Assisted regeneration	0.053	0.098	0.012	0.784
Physical infrastructure	0.139***	0.000	-0.149*	0.011
Residue addition	-0.061	0.093	0.116*	0.013
Mix measures	-0.328***	0.000	0.176*	0.013
Balaka District	0.049	0.518	0.011	0.900
Nsanje District	0.068	0.148	-0.504***	0.000
Thyolo District	0.041	0.389	-0.115	0.056
Zomba District	0.071	0.200	0.165*	0.027
Generalized residual	0.041	0.697	-0.094	0.547
Number of observation	807.000		770.000	
Log-pseudo likelihood	-429.635		-645.262	
Wald Chi2	173.030***	0.000	536.380***	0.000
Pseudo-R2	0.214			
Sigma			0.561***	0.000

Significance levels: * < 10%; ** < 5%; *** < 1%
Note: Chikwawa District is the base category.
Source: Authors' calculation using Stata 15MP

4.5 CONCLUSION

Climate change and extreme weather fluctuations have prompted massive global food security challenges in the developing world, especially in Sub-Saharan Africa. With increasing international aid going toward climate financing, the need to identify solutions for some of the provocative questions about how the impacts of CSA could better translate into tangible outcomes such as agricultural yields remain palpable. Such solutions could shed some light on how to tackle the adverse effects of climate change on rural communities in developing countries. An important strategy is the identification of pathways for channeling the impact of CSA interventions such as community-level watershed development that eventually result in human development.

This study has estimated the effects of agroforestry adoption as an impact pathway for participation in CSA programs, on maize yield, an important parameter as it is one measure of two food security indicators—availability and access. We used survey data from a large USAID-funded CSA intervention to estimate the effect of program participation maize yield per acre. The WALA project promoted climate-smart practices including agroforestry in order to reduce environmental degradation and food insecurity among rural communities living on marginal lands. WALA spanned eight districts in southern Malawi and occurred from 2009 to 2014.

Using a double hurdle specification with CF as the main analytical technique, the study finds statistically significant effects of agroforestry adoption as an impact pathway for participation in CSA interventions. In particular, we find that conditional on agroforestry adoption, CSA program participants would realize maize yield increases of 31% on average.

Although the application of a double hurdle model is not new, this study is among the first to use a double hurdle model to analyze agroforestry adoption as a pathway for the impact of CSA intervention. It thus presents a framework for future research on the impacts of various CSA interventions conditional on agroforestry—related parameters as pathways for CSA impacts.

This study has policy implications for improving agricultural yields by incorporating agroforestry in CSA programs in general and promoting their adoption as part of the CSA program. Moreover, the study could be useful for similar developing country contexts such as dryland areas in other Africa countries and elsewhere.

The availability of panel or pooled cros-sectional data could significantly this study.

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CHAPTER 5:

SUMMARY

The overarching goal of this dissertation research was to estimate the adoption of climate-smart agriculture (CSA), the impact of CSA adoption on food security through crop yields and household incomes, and to determine possible pathways through which CSA affects yields in southern Malawi.

Global estimates show that climate change and extreme weather events pose major food security and other international development challenges (World Economic Forum, 2018). For example, the number of undernourished people across the world is estimated to have increased from 777 million in 2015 to 815 million in 2016, with the majority living in developing countries vulnerable to extreme weather shocks (FAO et al., 2017).

CSA is widely viewed as an approach that entails prudent agricultural practices capable of minimizing environmental degradation while adapting agricultural systems to harsh new realities ushered in by climate change and more frequent extreme weather conditions (FAO, 2010; Lipper et al., 2014; Torquebiau et al., 2018). The approach is particularly crucial for developing countries such as those in Africa where climatic stress increasingly wreaks havoc on agricultural systems (FAO et al., 2017; Kpadonou et al., 2017; Sommer et al., 2018; Ubilava, 2018). A recent example is the El Niño droughts in southern Africa, which destroyed crop yields in several countries including Republic of South Africa, Zimbabwe, and Malawi, the focus of this dissertation, among others (World Bank Malawi Office, 2016; World Food Programme, 2017; Ubilava, 2018).

In Sub-Saharan Africa (SSA), an analysis of CSA adoption and associated impacts is crucial due to rapid environmental degradation and low financial resources that hinder national governments from effectively implementing and monitoring climate adaptation and mitigation policies. There is a particular need to understand the effectiveness of the billions of dollars in climate financing the international community has invested over the past decade. This need is necessary not only to advance theoretical and empirical knowledge of aid effectiveness for CSA and other climate-related projects but also to inform improved aid allocation and project implementation. Investment in this area is projected to climb to US$100 billion by 2020 (World Bank, 2015; Dinesh et al., 2017) and will likely increase further as the international community strives to reach the 2030 sustainable development goals (SDGs).

This dissertation has provided an in-depth examination of one exemplar form of this broader funding landscape, the US Agency for International Development (USAID)-funded Wellness, and Agriculture for Life Advancement (WALA) project. Implemented from 2009 to 2014 at a total cost of US$86 million, the WALA project was operational in eight southern Malawian districts and promoted several CSA practices such as agroforestry, stone bunds, and water absorption trenches within its area of intervention.

Despite efforts such as WALA, CSA adoption and the identification of CSA-related impacts remain low in many contexts across the developing world. My review of a growing literature on CSA, climate change, environmental management, and international development aid revealed several important gaps. I have worked to narrow these gaps and build knowledge in this important area of research and policy through the three papers in my dissertation.

The first paper (Chapter 2) contributes to filling the important gap of conceptual clarity that was lacking in the extant literature on CSA practices with the highest probability of adoption, given the wide array of CSA practices. To make this conceptual leap, I developed a farm-level CSA typology consisting of six categories—residue addition, non-woody plants, assisted natural regeneration, woody plants, physical infrastructure, and mixed measures—based on a thorough review of the extant literature. The typology and its underlying literature enabled me to generate testable hypotheses that I then empirically tested using data from a primary survey of 808 smallholder farm households in the WALA intervention area. I used recursive bivariate probit (RBP) for the empirical application to analyze the adoption probabilities of four out of six categories in the typology that WALA promoted. These included non-woody plants, assisted regeneration practices, woody plants, and physical infrastructure. I then used propensity score matching for robustness checks on the main estimates.

The analyses in Chapter 2 confirmed my hypotheses that under an externally supported CSA intervention, farmers would be more likely to adopt resource-intensive CSA categories (in this case, physical infrastructures and woody plants) than less resource intensive ones (in this case, assisted regeneration and non-woody plants). Accordingly, through the RBP estimates, I found that the average treatment effects on the treated for physical infrastructures and woody plants were 94%, and 61%, respectively compared to 49.7% and 41% for assisted regeneration and non-woody plants, respectively. The results from propensity score matching (PSM) followed the same trend. These results suggest that participation in the CSA program under WALA caused farmers to adopt more of the resource-intensive CSA categories that they would otherwise find difficult to adopt due to the high transaction costs of adoption.

The second paper (Chapter 3) performs an empirical analysis of CSA adoption to demonstrate the agricultural productivity and income effects of CSA (important goals of CSA) in the WALA intervention in southern Malawi. I used endogenous switching regression for that analysis on the same dataset as in Chapter 2. I found positive and statistically significant yield and income effects of at least 90% and 41%, respectively. Thus, Chapter 3 confirms that there are significant benefits of CSA adoption to food security through maize yield and household incomes in the WALA project area. I also found negative selection bias in CSA adoption, which implies that smallholder farmers with below-average yields and household incomes are more likely to adopt CSA in the research setting. Thus, policies that enhance CSA adoption will improve food security through higher crop yields and household incomes of smallholders in this setting.

The third paper (Chapter 4) contributes to narrowing the empirical evidence gap in the pathways through which CSA projects generate effects. Using the same datasets as I used in Chapters 2 and 3, I applied a double hurdle (DH) model with a control function to estimate the impact of CSA program participation on agricultural yields, conditional on agroforestry adoption as a CSA impact pathway. Program participants who adopted agroforestry saw their yields increase by an average of 31%. Chapter 4, thus, has a policy implication that mainstreaming externally supported CSA programs into smallholder agriculture could yield positive benefits to dryland communities such as southern Malawi and elsewhere.

In conclusion, the findings from the three papers in this dissertation show considerable degrees of heterogeneity in CSA adoption by category, the impact of adoption, and at least one pathway—agroforestry adoption—that could effectively link CSA programs/interventions with food security and other impacts in Malawi and beyond in similar climatic contexts. The results show that climate-related aid can be effective in spurring not only the adoption of more labor and other resource intensive climate-smart agriculture practices but also in increasing agricultural yield, boosting incomes, and improving overall food security, particularly for marginalized communities. The analyses presented here also demonstrate the need for further robust impact assessment of development interventions at the intersection of the environment, natural resources, and agriculture. In addition to the conceptual and empirical contribution of my dissertation, this work has significant policy implications for sustainable rural development in Malawi and elsewhere in Africa and beyond.

There are several possible extensions of this dissertation research including the following. First, there can be a case-by-case analysis of the adoption and impacts of specific CSA categories including all the six (6) categories in the typology (given data availability) to determine which CSA categories provide higher economic gains to smallholder farmers in SSA and elsewhere. To that end, one could utilize a multinomial endogenous treatment effect, which has been extensively applied in other empirical studies such as Asfaw et al. (2016) in Malawi, Manda et al. (2016) in Zambia, and Teklewold et al. (2017) in Ethiopia. Second, an analysis of potentially multiple pathways for concurrent impacts of CSA can be outstanding. Such analyses could utilize several DH models with control functions, or other state-of-the-art econometric methods such as a computable general equilibrium modelling. Third, this study can improve through an analysis of biophysical impacts of the CSA adoption through the WALA project and similar other externally supported projects, and to analyze the potential synergies and trade-offs between such impacts and the socio-economic ones that have been the subject of this study. Furth, this dissertation can extend to an analysis of the impacts of farmer extension facilitators in enhancing both CSA adoption and food security outcomes in the WALA intervention area because they were essential part of the project’s outreach to farmers. Finally, future research could examine the durability of externally funded agriculture and natural resource programs designed to address the challenge of climate change.

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GENERAL APPENDICES

APPENDIX A: INSTITUTIONAL REVIEW BOARD EXEMPTION LETTER AND STAMPED CONSENT FORM

APPENDIX B: FURTHER INFORMATION ABOUT THE WELLNESS AND AGRICULTURE FOR LIFE ADVANCEMENT (WALA) PROJECT

APPENDIX C: LIST OF RESEARCH ASSISTANTS (ENUMERATORS) AND THEIR INSTRUCTIONS ON DATA COLLECTION

APPENDIX D: PHOTOS FROM THE FIELDWORK

APPENDIX E: HOUSEHOLD-LEVEL QUESTIONNAIRE IN ENGLIGH AND CHICHEWA

APPENDIX F: KEY INFORMANT INTERVIEW GUIDE IN ENGLIGH AND CHICHEWA

APPENDIX A:

INSTITUTIONAL REVIEW BOARD EXEMPTION LETTER AND STAMPED CONSENT FORM

UNIVERSITY OF ILLINOIS
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RE: *An Impact Evaluation of the Adoption of Climate Smart Agriculture in Southern Malawi: Linking Agricultural Extension to Environmental Conservation and Food Security*
IRB Protocol Number: 16988

Dear Dr. McNamara:

Thank you for submitting the completed IRB application form for your project entitled *An Impact Evaluation of the Adoption of Climate Smart Agriculture in Southern Malawi: Linking Agricultural Extension to Environmental Conservation and Food Security*. Your project was assigned Institutional Review Board (IRB) Protocol Number 16988 and reviewed. It has been determined that the research activities described in this application meet the criteria for exemption at 45CFR46.101(b)(2).

This determination of exemption only applies to the research study as submitted. Please note that additional modifications to your project need to be submitted to the IRB for review and exemption determination or approval before the modifications are initiated.

Copies of the attached, date-stamped consent form(s) are to be used when obtaining informed consent. If there is a need to revise or alter the consent form(s), please submit the revised form(s) for IRB review, approval, and date-stamping prior to use.

Exempt protocols will be closed and archived five years from the date of approval. Researchers will be required to contact our office if the study will continue beyond five years. If an amendment is submitted once the study has been archived, researchers will need to submit a new application and obtain approval prior to implementing the change.

We appreciate your conscientious adherence to the requirements of human subjects research. If you have any questions about the IRB process, or if you need assistance at any time, please feel free to contact me at OPRS, or visit our website at http://oprs.research.illinois.edu

Sincerely,

Dustin L. Yocum, MA, CIP
Human Subjects Research Specialist, Office for the Protection of Research Subjects

U of Illinois at Urbana-Champaign • IORG0000014 • FWA #00008584
telephone (217) 333-2670 • *fax* (217) 333-0405 • *email* IRB@illinois.edu

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AT URBANA-CHAMPAIGN

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AN IMPACT EVALUATION OF THE ADOPTION OF CLIMATE SMART AGRICUTLURE IN SOUTHERN MALAWI: LINKING AGRICULTURAL EXTENSION TO ENVIRONMENTAL CONSERVATION AND FOOD SECURITY

Oral Informed Consent Form

Hello, my name is _______, and I am a researcher from the University of Illinois at Urbana Champaign. I'm doing a research on the adoption of climate smart agriculture (CSA), and agricultural extension outcomes in this community. I want to learn about your experiences regarding soil and water conservation, as well as other environmental management practices as part of CSA. I'm not selling anything or offering any services right now, but we hope that by understanding CSA and agricultural extension delivery in southern Malawi, it is possible that various organizations can provide better CSA and agricultural extension services in the future. Your participation is completely voluntary. Choosing to participate will not increase your opportunities for any future services. Similarly, choosing not to participate will not decrease your opportunities for future benefits or services. If you choose to participate, I'll ask you a number of questions about your farming activities and your opinion about CSA and agricultural extension services in this community. You must be 18 years or older to participate in this study.

You can choose not to answer any question you wish, but we hope that you'll choose to answer all of the questions to give us a more-complete picture of CSA and agricultural extension delivery here. Also, you can choose to stop the interview at any time you wish, and you do not have to participate to the end, if you change your mind. I don't anticipate any risks from your participation beyond those risks encountered in everyday life.

In general, we will keep your answers confidential, and not tell anyone any information about you. No one in your community will know what your answers are unless you tell them. Only the research staff will see your answers. When this research is disclosed or published, no one will know that you were in the study. Your answers will be grouped with other farmers to give an overall picture of CSA and agricultural extension in this area. However, laws and university rules might require us to disclose information about you. For example, if required by laws or university policy, the following people or groups may see or copy the study information:

- The university committee and office that reviews and approves research studies – the Institutional Review Board (IRB) and office for Protection of Human Subjects at our university.
- The financial sponsors of this study
- University and state auditors, and Department of the university that oversees research at the University of Illinois, Urbana-Champaign
- The federal government regulatory agencies such as the Office of Human Protection in the Department of Health and Human Services

Do you have any questions about this study or your participation?

Do you agree to participate in this interview? ***Yes (), No ().***

If *"No"*, don't proceed with the survey for this individual.

Thank you for your time today.

University of Illinois at Urbana-Champaign
Institutional Review Board

Approved: 7-6-16
IRB #: 16988

APPENDIX B:

FURTHER INFORMATION ABOUT THE WELLNESS AND AGRICULTURE FOR LIFE ADVANCEMENT (WALA) PROJECT

Table B1: WALA project districts and corresponding implementing agencies in the WALA consortium

No.	**WALA's operational district**	**Key Implementing Partner Agency**
1	Balaka	Project Concern International
2	Chikwawa	Chikwawa Diocese
3	Chiradzulu	Save the Children
4	Machinga	Project Concern International Emmanuel International
5	Mulanje	Africare
6	Nsanje	Total Land Care
7	Thyolo	World Vision
8	Zomba	Save the Children Emmanuel International

Source: Secondary data including desk survey of final evaluation report of WALA, 2014.

Table B2: WALA'S strategic objectives and target outcomes

WALA's Strategic Objectives (SOs)	Main focus & components	Targets & beneficiaries	Key activities per component
SO1: Maternal & Child Heath Nutrition (MCHN) to target under-5 children who are presumed to represent typical households	Improved Nutritional Status of communities. Designed for health, hygiene, and nutrition (HHN) outcomes of women and children.	1.Targets nutrition behavior changes 2.Targets every households with pregnant and/or lactating mothers 3. Targets all children under the age of 5 years (commonly known as under 5's).	Supplementary Feeding of all who get referred from clinics, hospitals, or Health Surveillance Assistants (HSAs) in the community
SO2: Human and community development activities	Improved livelihood security and communities' economic wellbeing through collective action including village Savings and Loans (VSL)	initially targeted smallholder farmers owning less than one hectare of land but have opened up participation to all farming households that are willing to engage in WALA activities	- Small-scale Irrigation scheme - VSL - Enterprise development
SO3: Natural resource management and community resilience against drought & disaster risks by improving capacity to withstand shocks.	Enhancing food security and environmental sustainability in the project area through irrigation, watershed development at the community level, with knowledge/skills trickling down to individuals farmers' plots.	All communities that meet the selection criteria Food for work provided at community level watershed development Individual farmers implement CSA practices on their plots without additional incentives other than extension services	- Agroforestry - Apiculture - CCTs - Check dams - Marker ridges - Stone bunds - Vetiver grass - Water absorption trenches

Source: Desk survey of final evaluation report of WALA, 2014

Table B3: Description of CSA practices under WALA

CSA practice	Description	Level of implementation
Agroforestry	- A combination of fruit and fertilizer trees along with indigenous trees. - The Cassod, Lebbeck, and *Acacia polylicatha species were among the* most common trees promoted. - Mango, papaya, banana, and peach were the common fruit trees promoted (Reichcart, 2014, p. 6).	Community level implementation with extension services on farmers' fields. WALA provided as seedlings to communities.
Apiculture	- The rearing of honey bees not only to empower communities for joint economic activities, but also as a way of enhancing environmental protection by avoiding deforestation.	Community level
Check dam	- Stone walls built against a deep or shallow gully in a field or around a field. The aim is to slowly remove the "gully" by gradually sieving soils and manure into it. - The standard for check dams is "suitability to the local context especially regarding the "flow rate" in of the "dams" targeted. This is a vital feature of CSA approach in general - WALA-promoted specifications for check dams to have dimensions ranging from 50 to 150 cm high about 150 cm wide whereas the length depends on the situation/context. - However, many of the check dams were between 2 to 12 meters in long.	Community level implementation with extension services on farmers' individual fields/plots
Maker ridges	- They are ridges erected of planting crops in a furrow, usually along contours - Designed for water retention in a plot and gradual percolation into the soil, thereby enhancing improved soil moisture content - They are vital in ground water recharge through infiltration of surface water into aquifers. - Usually, crops are planted on erected ridges along contour lines at about 75 cm spacing. - People usually practice markers ridges in combination with cover crops such as vetiver grass in order to protect the ridges.	Community level implementation with extension services on farmers' fields

Table B3 cont'd

CSA practice	Description	Level of implementation
Stone bunds	- They are ubiquitous in moderate-steep plot settings that have lots of stones. - They are usually around 1 high and wide. - These are moderate walls of stones erected against run-off. - They also enhance water percolation into the soil, and contribute to groundwater recharge, moisture retention, and evenly distributing water across a lot.	Community level implementation with extension services on farmers' fields
Continuous contour trenches	- They include moderately long drainages dug laterally on contour lines in farmers' plots. - In Malawi, they are known locally as "swales". - They help to slow down erosion and enhance infiltration into the soil. - They aide in nutrition and soil conservation by curbing erosion. - They usually between 30 to 60 centimeters deep and 30 cm wide.	Community level implementation with extension services on farmers' fields
Vetiver grass	- A special grass used as cover crop in conjunction with other CSA practices to both retain soil moisture, and improve soil nutrients. - Some are known to be nitrogen enhancing through their root nodules	Community level implementation with extension services on farmers' fields
Water absorption trenches	- These are usually aimed at water collection and retention within the filed within moderately to large basis for gradually supplying the entire field or portions thereof. - They are dug around a field instead of within specific plots dues to their "large sizes". - The dimension is usually at 60 cm deep, and 1m, and can be up to 10 meters long. - Meant to gather surface water from wider areas around the plot for a longer period of use over time. - Can be dug across a slope to enhance better efficiency.	Community level implementation with extension services on farmers' fields

Source: Author's secondary data collection in southern Malawi, 2015/16.

APPENDIX C:

LIST OF RESEARCH ASSISTANTS (ENUMERATORS) AND THEIR INSTRUCTIONS FOR DATA COLLECTION

Table C1: List of enumerators

No	First name	Last name	Qualification	Institution	Role/position
1	Thaskani	Chipeta	MSc.	LUARNA	Lead Enumerator
2	Zephania	Nyirenda	MSc.	LUARNA	Lead Enumerator
3	Steven	Wassili	MSc.	LUARNA	Enumerator
4	Hannah	Ganunga	MSc.	LUARNA	Enumerator
5	Kelita	Phambala	BSc	LUARNA	Enumerator
6	Chikonde	Kasenka	BSc	LUARNA	Enumerator
7	Yohane	Fabiano	BSc	LUARNA	Enumerator
8	Hope	Mndala	BSc	Chancellor College	Enumerator
9	Thanko	Juma	BSc	Chancellor College	Enumerator
10	Magdalene	Njola	BSc	Chancellor College	Enumerator
11	Hlupie	Meija	BSc	Chancellor College	Enumerator
12	Chancy	Kasungo	Diploma	Malawi Inst. of Tech.	Enumerator
13	Victor	Salousi	Diploma	-	Enumerator
14	Gibson	Masanjala	BSc	University of Malawi	Enumerator

Table C2: Local names for common livestock and crops

SOME LIVESTOCK CHICHEWA NAMES	
English	**Chichewa**
1. Cattle	Ng'ombe
2. Goat	Mbuzi
3. Pig	Nkhumba
4. Chicken	Nkhuku
5. Sheep	Nkhosa
6. Rabit	Kalulu
7. Guinea Fowl	Nkhanga
8. Turkey	Nkhukudembo
9. Donky	Bulu
SOME CROP CHICHEWA NAMES	
1. Maize	Chimanga
2. Ground nuts	Mtedza
3. Sorghum	Mapira
4. Tobacco	Fodya
5. Millet	Mchewere
6. Rice	Mpunga
7. Tomato	Matimati
8. Beans	Nyemba
9. Sweet potato	Mbatata
10. Potato	Kachewere
11. Cassava	Chinangwa
12. Cow peas	Khobwe
13. Pigeon Peas	Nandolo
14. Sun flower	Mpenda dzuwa

Source: From Author’s secondary data in the WALA area.

APPENDIX D: PHOTOS FROM THE FIELDWORK

Figure D1: Author standing by a signpost of the WALA watershed (i.e., CSA) intervention in the study area.

Figure D2: Author supervising a personal interview in the Malawi's main local dialect of Chichewa, at Mparman Grouped Village Headman in Chikwawa district

Figure D3: Author in a maize plot to collect soil samples after supervising a personal interview with the farmer pictured in Figure D2

Figure D4: Author collecting secondary data from the Agricultural Extension Development Coordinator in Massambajati Extension Planning Area, Thyolo district

Figure D5: Author conducting key informant interview with community representative at Mperma Grouped Village Headman in Chikwawa district

Figure D6: Author listening to a farmer explain the benefits of water absorption trench on his farm at Mbangu Grouped Village Headman, Zunde Extension Planning Area in Nsanje district

Figure D7: Author with a smallholder farm family practicing agroforestry at Chikololere Grouped Village Headman, Bazali Extension Planning Area in Balaka district

Figure D8: Author having a community briefing session at Gombe Grouped Village Headman, Thekeran Extension Planning Area in Thyolo district.

Figure D9: Author inspecting agroforestry nursery at Mbangu Grouped Village Headman, Zunde Extension Planning Area in Nsanje district.

Figure D10: Author inspecting check dams at Mbangu Grouped Village Headman, Zunde Extension Planning Area in Nsanje district.

Figure D11: Author inspecting a continuous contour trench at Mbangu Grouped Village Headman, Zunde Extension Planning Area in Nsanje district.

Figure D12: Author inspecting stone bunds at Mbangu Grouped Village Headman, Zunde Extension Planning Area in Nsanje district.

APPENDIX E:

HOUSEHOLD-LEVEL QUESTIONNAIRE IN ENGLIGH AND CHICHEWA

E1. English version of the household-level questionnaire

E.1.1. District code |___|___|___|

E.1.2. Traditional Authority (TA) |___|___|___||___|

E.1.3. Group Village Head (GVH) ID |___|___|___|

E.1.4. Village/community name |_______________|

E.1.5. Community category (Treatment = 1)

E.1.6. Household ID |___|___|___|

E.1.7. Interview date |___|___|___|

E.1.8. Questionnaire number |___|___|___|

E.1.9. Time interview started |___________|

E.1.10. Time interview ended |___________|

E.1.11. Interviewer name and ID ___________|

District codes

Balaka	= 01
Chikwawa	= 02
Nsanje	= 03
Thyolo	= 04
Zomba	= 05

EPA codes

Bazalie	= 0101
Livunzu	= 0201
Mitole	= 0202
Makhanga	= 0301
Zunde	= 0302
Massambajati	= 0401
Thekerani	= 0402
Thondwe	= 0501

Treatment GVH codes

Chicololere	= 010101
Kasisi	= 020101
Mparma	= 020201
Gatorma	= 030101
Mbangu	= 030201
Nkusa	= 040101
Gombe	= 040201
Mbeluwa	= 050101

Control GVH codes

Mpoto	= 010102
Chavala	= 020102
Nyambaru	= 020202
Alufazema	= 030102
David	= 030202
Mangwalala	= 040102
Chalonda	= 040202
Kutambala	= 050202

Instruction to Enumerator: Before the interview, please use the following script to obtain a consent for interview.

Hello. My name is ____, and I am a research assistant for a doctoral dissertation research conducted by a PhD student from University of Illinois at Urbana-Champaign. We are interested in understanding the effects of climate smart agriculture (CSA) in this community. We do not represent any government agency or NGO in Malawi, or any political party. We want to understand the experiences of farmers like you, in various climate smart agricultural techniques in this community. I would like to speak to the primary person in charge of agricultural production decision-making for this household.

Then read the oral consent letter to obtain oral consent before proceeding with interview.

E.1.12. Respondent's name (optional) ____

Assessment of household perception of climate smart agriculture (CSA) practices

Question	**Response**	**Question**	**Response**
1. Approximately, age? *Enumerator, please note that respondents do not need to give their exact age.*	i. 18 – 25 =1 ii. 26 – 35 =2 iii. 36 – 45 =3 iv. 45 – 60 = 4 v. Above 60 =5	2. How long has your household been in this community?	i. less than 2 years ( ), **stop interview.** ii. 2 – 5 years ( ) iii. 5-10 years ( ) iv. More than 10 years ( )
3. Respondent's major occupation	Farming = 1 Other = 0, specify ………. ……………………………... ……………………………...	4. Respondent's role in the Household.	Head = 1 Spouse = 2 Son = 3, daughter = 4 Other, (specify)……………..

5. Marital status	Married = 1, Other = 0	6. Educational level	i. University graduate = 1 ii. Polytech education = 2 ii. Secondary education = 3 iii. Primary only = 4 iv. None formal education = 5
7. What is the total number of people in this household?	<u>Category</u> <u>Number</u> i. Men = ii. Women = iii. Children =	8. How many people in this household are: - In primary school - In secondary school - polytechnic level - In university	Specify amount
9. What is the main livelihood source of your household?	i. Crop farming only = 1 ***(skip qs. 34 – 36)*** ii. Livestock only = 2 ***skip to 34***). iii. Crops & animals = 3 iv. Other (specify)………… ……………………………..	10. If crops only, how many types of crops do you often grow per year (each rainy season). *Enumerator, refer to note on cropping season and crop codes.*	Enter crop codes
11. How many parcel(s) do you own or have access to?	Specify amount	12. From the parcel(s) you own, how many plots do you often cultivate?	Enter numbers
13. How many plots did you cultivate this year (2016)?	Specify amount/quantity.	14. What main crop(s) did you cultivate on your plot(s) this year (2016)?	Enter crop code
15. In general, what is the total size of your parcel(s) or plots(s)?	i. Less than 1 acre = 1 ii. 1.5 – 5 acres = 2 iii. 5 – 10 acres = 3 iv. More than 10 = 4	16. Does any of your plots have a slope?	Yes = 1 No = 0, skip to 20.
17. How many of your plots have slopes that are: - Very steep - Moderately steep - Flat	<u>No. of plots</u> <u>Size</u>	18. Do you think there is any effect of farming on a sloppy land?	Yes = 1 No = 0, skip to 20.

<table>
<tr><td>19. What effect(s)?</td><td>i. Labor intensive ( )
ii. Low water availability ( )
iii. Poor soil fertility ( )
iv. Other (specify) ………..
…………………………</td><td>20. List the number of plots you cultivated in the past five years, and the sizes in acres.
- 2011
- 2012
- 2013
- 2014
- 2015</td><td><u>No of plots</u> <u>Size (in acres)</u>
______ ______
______ ______
______ ______
______ ______
______ ______</td></tr>
<tr><td>21. What cropping system(s) do you practice on your plot(s)?
i. Sole/mono cropping
ii. Mixed cropping
iii. Other (specify)……….……………
……………………………..
……………………………..</td><td><u>Yes = 1, specify</u> <u>No = 0</u></td><td>22. In the past five years, list the kinds of crops cultivated on your plot and the acreage you cultivated.
- 2011
- 2012
- 2013
- 2014
- 2015</td><td>Refer to crop codes
<u>Crop</u> <u>Plot size</u>
______ ____________
______ ____________
______ ____________
______ ____________
______ ____________</td></tr>
<tr><td>23. During the past five years, how fertile was/were your plot(s)
- 2011
- 2012
- 2013
- 2014
- 2015</td><td>Not Fertile (1) | Fertile (2) | Very fertile (3)
______ ______ ______
______ ______ ______
______ ______ ______
______ ______ ______
______ ______ ______</td><td>24. In general, do you think that the fertility level of your plots changed over the past five years (2011 to 2015)?</td><td><u>Plot</u> <u>Yes =1</u> <u>No = 0</u></td></tr>
<tr><td>25. If yes, has the change been positive or negative?</td><td>Positive = 1
Negative = 0, skip to 30.</td><td>26. What positive changes occurred?</td><td>i. Soil fertility improved ( )
ii. Water retention increased ( )
iii. Higher soil moisture ( )
iv. Higher amount of soil cover crops ( )</td></tr>
</table>

27. In your opinion, which factors influenced this change?	i. Better soil management practices ( ) ii. Higher focus on erosion control ( ) iii. Higher focus on soil cover ( ) iv. Other (specify)………… ……………………………	28. Has you implemented any soil, water, or land management practice on your plot in the past - One year? - Two years? - Three years? - Four or more years?	Yes = 1 No = 0
29. What improved soil management practices have you, or someone you know, applied on this land over the past five years (2011 – 2015)?	i. Planting cover crops ( ) ii Catchment management ( ) iii. Agroforestry ( ) Iv. Other (specify) ……….. …………………………	30. What negative changes did you experience on your plots in the past five years (2011–2015)?	i. Loss of available fertile lands due to soil loss to erosion ( ) ii. Loss of soil nutrients ( ) iii. Lack of adequate soil moisture for crop growth ( ) iv. Other (specify) …………….. ………………………………
31. In the past five years, did your household hire labor for your cropping activities?	Yes = 1 No = 0, skip to 33.	32. In the past five years (or rainy) seasons, what was your total expenditure on the following activities? - Planting - Weeding - Harvesting - Other (specify)……………..	List the amounts per acre per plot, per cropping season, and year. <u>Year</u> <u>No. of plots</u> <u>Cost</u>

33. If you didn't hire any outside labor, how much do you think you would have spent on the following activities over the past five years? - Planting - Weeding - Harvesting - Other (specify……………. ………………………………	Cost per acre, per plot, per year. No of Plots, Year Cost	34. How many animals do you have in total, and how long have you had them? Please list all in the next box. *Enumerator:* *(1) Refer to note for the definition and meaning of animal.* *(2). Skip qs. 26 – 33, if respondent's answer in question 9 was "1" crops only.*	Specify as follows: Animal #/amount Age
35. How much do you often spend on each category of animals per month, or year?	Animal Year Cost	36. What farming system do you use for your animals?	Response: i. Free range = 1 ii. Controlled grazing in restricted areas = 2 iii. Intensive = 3 iv. Other (specify) ……………………………….. ……………...........................
37. In the past 3- 5 years, how much did your household spend on the following? - Food = 1 - Health care = 2 - Schooling/education = 3 - Farming operations = 4 - Transportation = 5 - Other (specify) ……………	Enter activity code and cost under time period Activity, Month/Term Year	38. Were you able to adequately address all your household expenditure requirements for? - Food - Health - Education/Schooling - Farming operations - Transportation	Yes = 1, skip to 41. No = 0

39. If no, why?	- Inadequate cash due to low yields ( ) - Too much expenditure on soil improvement work ( ) - Other (specify) …………... ……………………………	40. What main livelihood improvement(s) do you and your household wish to obtain in the next coming years?	i. Better access to food ( ) ii. Higher crop yields ( ) iii. Better access to drinking water ( ) iv. Other(specify) …………… ……………………………
Assessment of agricultural extension services			
41. Do you have access to regular agricultural information in this community?	i. Yes = 1 ii. No = 2	42. What is your main source of agricultural information?	i. WALA = 1 ii. UBALE = 2 iii. DAES = 3 iv. NGO (state) ……………...
43. Do you have access to an extension agent in this community?	Yes = 1 No = 0, skip to 49.	44. In the past cropping season, how many times did you interact with an extension agent in this community?	List
45. In the past cropping season, what main service(s) did your household obtain from extension agents in this community?	i. Planting patterns = 1 ii. Water mgt = 2 iii. Weeding = 3 iv. Pest control = 4 v. Other (specify) …………….	46. How do you rate the quality of agricultural information you received in the past two years?	i. Ineffective ( ) ii. Effective ( ) iii. Very effective ( )
47. How do you rate the quality of agricultural information you received in the past three years?	i. Ineffective ( ) ii. Effective ( ) iii. Very effective ( )	48. How do you rate the quality of agricultural information you received in the past five years?	i. Ineffective ( ) ii. Effective ( ) iii. Very effective ( )
49. Do you pay for agricultural information services?	Yes = 1 No = 0 Skip to 51	50. If yes, how much do you pay?	List amount.

Assessment of knowledge and practice of CSA			
51. Do you know of any watershed in this community? (Enumerator, please explain or describe a watershed to the respondent).	Yes = 1 No = 0, skip to 55.	52. If yes, do you farm in, or around a watershed in this community?	Yes = 1 No = 0 Skip to 54
53. What is the distance from your farm(s)/plots to the nearest watershed?	Less than 1km i. 1– 3km ii. 3 – 5 km iii. more than 5km	54. Over the past five years, did any watershed development occured in this community?	Yes = 1 No = 0
55. Do you know about CSA technology? Enumerator, refer to your note on CSA approach and practices.	Yes = 1 No = 0 Skip to 64.	56. What do you know about CSA practices?	Explain ………………………………. ………………………………. ………………………………. ………………………………. ……………………………….
57. When did you first learn about CSA?	i. Before 2009 = ( ) ii. 2009 – 2014 = ( ) iii. After 2014 = ( ) iv. Other (specify) ………… …………………………..	58. How did you learn about CSA?	i. WALA = 1 ii. UBALE = 2 iii. DAES = 3 iv. Other (specify)...…....…………….

59. In the last five years, have you practiced any CSA technique(s) on your plot(s)?	Yes = 1 No = 0	60. Which kinds of CSA practices did you implement in your plot(s) between 2009 and 2015?	Tick all that apply. - Stone bunds ( ) - CCTs ( ) - WATs ( ) - Marker ridges ( ) - Agroforestry ( ) - Vetiver grass ( ) - Irrigation canals ( ) - Other (specify)………... …………………………
61. Why did you implement the above CSA practices?	- To reduce runoff = 1 - To harvest water = 2 - Increase crop yield = 2 - Other (specify) ………… …………………………… ……………………………..	62. Are there any CSA practices on your plot(s)?	Yes = 1 No = 0, skip to 64
63. Which kinds of CSA practices do you currently have at your plot(s)?	Tick all that apply. - Stone bunds ( ) - CCTs ( ) - WATs ( ) - Marker ridges ( ) - Agroforestry ( ) - Vetiver grass ( ) - Irrigation canals ( ) - Other (specify)…….. ……………………..	64. Do you know about WALA watershed development in this community?	Yes =1, No, skip to 70
65. Did your household receive any support from the WALA watershed treatment program?	Yes = 1 No = 0, skip to 73.	66. Which support(s) did you receive from the WALA watershed program?	List all.

67. In the past five years, did you, or a member of your household participate in any WALA watershed management programme in this community?	Yes = 1 No = 0, skip to 73.	68. If yes, what was your participation about?	- Stone bunds ( ) - CCTs ( ) - WATs ( ) - Marker ridges ( ) - Agroforestry ( ) - Vetiver grass ( ) - Irrigation canals ( )
69. When did you start having these CSA practices on your farm?	- 2011 ( ) - 2012 ( ) - 2013 ( ) - 2014 ( ) - 2015 ( )	70. Are there any CSA practices on your plot(s) that were not there before 2014?	Yes = 1 No = 0
71. Were there any CSA practices on your plot(s) in 2014 that are no longer there?	Yes = 1 No = 0	72. If yes, which one(s).	List
73. Assuming you had the option of practicing a combination of any of the following CSA techniques, which combination do you think will give you the highest yield for your crops? List in order of priority.	<u>Crop</u> <u>CSA combination</u> ______ ______________________________ ______ ______________________________ ______ ______________________________ ______ ______________________________ ______ ______________________________ *Enumerator, enter crop code from your notes*		Tick all the combinations: - Stone bunds - CCTs - WATs - Marker ridges - Agroforestry (trees on farm) - Vetiver grass Irrigation canals
74. Please give reason(s) for your answer.	Explain.		
Potential impact of CSA on agricultural yields and water availability.			
75. What was your total yield (in 50 kg bags) in 2010?	Amount	76. What was your total yield (in 50kg bags) in 2014?	i. 0 – 20 ( ) ii. 21 – 50 ( ) iii. 51 – 100 ( ) iv. 100 ( )

77. What was your total yield (in 50 kg bags) in 2015?	Amount	78. What was your total yield (in 50kg bags) in 2016?	i. less than 20 ( ) ii. 21 – 50 ( ) iii. 51 – 100 ( ) iv. 100 ( )
79. In the past five years (2011 – 2015) did you experience any change in yield? - 2011 - 2012 - 2013 - 2014 - 2015	In 50kg bags <u>Yes = 1 (amount)</u> <u>No = 0</u>	80. What do you think was most responsible for your experience? - availability of ground water due to reduced run-off - Increased percolation of rainwater - Better manure on soil surface - Other (specify)	Yes = 1 No = 0
81. Do you have a river around your plot(s)?	Yes = 1 No = 2	82. What is the usual depth of the river?	i. Ankle level ( ) ii. Knee level ( ) iii. Waist level ( ) iv. shoulder level ( ) v. Beyond normal height ( )
83. What is the current depth of the river?	i. Ankle level ( ) ii. Knee level ( ) iii. Waist level ( ) iv. Shoulder level ( ) v. Beyond normal height ( )	84. What was the depth of the river in 2015?	i. Ankle level ( ) ii. Knee level ( ) iii.Waist level ( ) iv. Shoulder level ( ) v. Beyond normal height ( )
85. What was the depth of river in 2014?	i. Ankle level ( ) ii. Knee level ( ) iii. Waist level ( ) iv. shoulder level ( ) v. Beyond normal height ( )	86. What was the depth of the river in 2013?	i. Ankle level ( ) ii. Knee level ( ) iii. Waist level ( ) iv. shoulder level ( ) v. Beyond normal height ( )

87. What was the depth of river between 2009-2012?	i. Ankle level ( ) ii. Knee level ( ) iii. Waist level ( ) iv. Shoulder level ( ) v. Beyond normal height ( )	88. Have you experienced any noticeable change(s) in the level of available water for your home use since you started participating in the WALA watershed management practices?	Yes = 1 No = 0
89. What specific changes in water level and availability have you and your family experienced?	List all	90. What do you think is responsible for this change?	List all.
Potential effects on food security			
91. Do you know about food security?	Yes = 1, No = 0	92. What do you know about food security?	List all that applies.
93. Before 2015, do you think you enjoyed food security?	Yes = 1, No = 0	94. Before 2014, how many of each of these foods did your household eat per week? - Maize (staple) - Fruits and vegetables - Sugar - Oils - Fish - Meat - Others (specify)…………… ……………………………..	Estimates

95. In 2015, how many of each of these foods did your household eat per week? Maize (staple) - Fruits and vegetables - Sugar - Oils - Fish - Meat - Others (specify)…………… ……………………………..	Estimates	96. Since 2016, how many of each of these foods did your household eat per week? - Maize (staple) - Fruits and vegetables - Sugar - Oils - Fish - Meat - Others (specify)…………… ……………………………..	Estimates
97. In 2014, what was your average weekly expenditure on: - Maize (staple) - Fruits and vegetables - Sugar - Oils - Fish - Meat - Others (specify)…………… ……………………………..	Estimates	98. In 2015, what was your average monthly expenditure on: - Maize (staple) - Fruits and vegetables - Sugar - Oils - Fish - Meat - Others (specify)…………… ……………………………..	

99. Since 2016, what is your average weekly consumption of: - Maize (staple) - Fruits and vegetables - Sugar - Oils - Fish - Meat - Others (specify)…………… ……………………………..	Estimates	100. Since 2016, what has been your average weekly expenditure on: - Maize (staple) - Fruits and vegetables - Sugar - Oils - Fish - Meat - Others (specify)…………… ……………………………..	Estimate
101. Since the 2014/2015 drought, what has been your average monthly consumption of: - Maize (staple) - Fruits and vegetables - Sugar - Oils - Fish - Meat - Others (specify)…………… ……………………………..	Estimate	102. Since the 2014/2015 drought. what has been your average monthly expenditure on: - Maize (staple) - Fruits and vegetables - Sugar - Oils - Fish - Meat - Others (specify)…………… ……………………………..	Estimate
103. Do you, or any member of your household ever feel that you will not have access to adequate food for your daily consumption for the next two days?	Yes = 1, No = 0	104. Do you, or any member of your household ever feel that you will not have access to adequate food for your daily consumption for the next one weeks?	Yes = 1, No = 0

105. Do you, or any member of your household ever feel that you will not have access to adequate food for your daily consumption for the next one month?	Yes = 1, No = 0	106. Do you, or any member of your household ever feel that you will not have access to adequate food for your daily consumption for the next three months?	Yes = 1, No = 0
Measures of households food insecurity access scale (HFIAS)			
107. In the last 30 days, did you worry that you or your household members would not have enough food?	Yes = 1, No = 0	108. In the last 30 days, were you or any household member not able to eat the kind of food you preferred because of lack of resources?	Yes = 1, No = 0
109. In the last 30 days, did you or any household member eat just a few kinds of food day after day due to lack of resources?	Yes = 1, No = 0	110. In the last 30 days, did you or any household member eat food that you preferred not to eat because of a lack of resources?	Yes = 1, No = 0
111. In the last 30 days, did you or any household member eat a smaller meal than you felt you needed because there was not enough food?	Yes = 1, No = 0	112. In the last 30 days, did you or any household member eat fewer meals in a day because there was not enough food?	Yes = 1, No = 0
113. In the last 30 days, did you or any household member go to sleep at night hungry because there was not enough food?	Yes = 1, No = 0	114. In the last 30 days, did you or any household member go a whole day without eating because there was not enough food?	Yes = 1, No = 0
115. In the last 30 days, was there ever no food at all in your household because there was not resources to get more?	Yes = 1, No = 0	116. In the last 7 days, did you worry that you or your household members would not have enough food?	Yes = 1, No = 0

117. In the last 7 days, were you or any household member not able to eat the kind of food you preferred because of lack of resources?	Yes = 1, No = 0	118. In the last 7 days, did you or any household member eat just a few kinds of food day after day due to lack of resources?	Yes = 1, No = 0
119. In the last 7 days, did you or any household member eat food that you preferred not to eat because of a lack of resources?	Yes = 1, No = 0	120. In the last 7 days, did you or any household member eat ate smaller meal than you felt you needed because there was not enough food?	Yes = 1, No = 0
121. In the last 7 days, did you or any household member eat fewer meals in a day because there was not enough food?	Yes = 1, No = 0	122. In the last 7 days, did you or any household member go to sleep at night hungry because there was not enough food	Yes = 1, No = 0
123. In the last 7 days, did you or any household member go a whole day without eating because there was not enough food?	Yes = 1, No = 0	124. In the last 7 days, was there ever no food at all in your household because there was not resources to get more?	Yes = 1, No = 0
125. In the last 24 hours, did you worry that you or your household members would not have enough food?	Yes = 1, No = 0	126. In the last 24 hours, were you or any household member not able to eat the kind of food you preferred because of lack of resources?	Yes = 1, No = 0
127. In the last 24 hours, did you or any household member eat just a few kinds of food day after day due to lack of resources?	Yes = 1, No = 0	128. In the last 24 hours, did you or any household member eat food that you preferred not to eat because of a lack of resources?	Yes = 1, No = 0

129. In the last 24 hours, did you or any household member eat smaller meal than you felt you needed because there was not enough food?	Yes = 1, No = 0	130. In the last 24 hours, did you or any household member eat fewer meals in a day because there was not enough food?	Yes = 1, No = 0
131. In the last 24 hours, did you or any household member go to sleep at night hungry because there was not enough food?	Yes = 1, No = 0	132. In the last 24 hours, did you or any household member go a whole day without eating because there was not enough food?	Yes = 1, No = 0
133. In the last 24 hours, was there ever no food at all in your household because there was not resources to get more?	Yes = 1, No = 0	134. In the last 24 hours, how much money did you spend on: - Maize (staple) - Fruits and vegetables - Sugar - Oils - Fish - Meat	Estimate
135. In the last 7 days, how much money did you spend on: - Maize (staple) - Fruits and vegetables - Sugar - Oils - Fish - Meat	Estimate	136. In the last 30 days, how much money did you spend on: - Maize (staple) - Fruits and vegetables - Sugar - Oils - Fish - Meat	Estimate

Section E.2: Assessment of actual soil quality

Instruction

Enumerator will say to the respondent; I would like to visit your main farm/plot to collect some soil samples from the ground in order to help us determine actual soil quality of your plot(s), based on a lab test. You, or a member of your household should take us to the field/plot(s) where you have been working for the past five years so we can sample the soils from there. Can you allow us to go and take a little dirt from your field/plot now?

- Yes = 1, If yes, proceed to collect soil sample from the field/plot(s).
- No = 0, stop interview and move on.

E.2.1. GPS coordinate of the plot

- Latitude
- Longitude

E.2.2. Other description of the plot.

- Distance from village ____
- Plot number (s) __________________
- Distance from the nearest treated/developed watershed =
- Distance from the nearest untreated/undeveloped watershed =
- Field/plot cultivated in 2015? Yes =1, No = 0
- If Yes, what crop(s) ____

- Cropping pattern over the five years?

E.2.3. Visual inspection: Do you see any of the following CSA techniques on this plot?

Question	**Response**	**Question**	**Response**
CSA practices	Yes =1 No = 2	If yes, specify the amount	Condition: Well functional = 1 Out of shape = 2
Water absorption trenches (WAT)			
Continuous contour trench (CCT)			
Marker ridges			
Stone bunds			
Agroforestry (trees on farms)			
Vetiver grass			
Irrigation canal			

B3. Sampling across the landscape: From across the field/plot collect soil samples for both physical and chemical properties using the following criteria:

E.3.1. Sample from the top of the landscape

GPS coordinate of the point in the plot

- Latitude
- Longitude
- 0 – 20 cm
- 20 – 40 cm

E.3.1.2. Sample from the middle of the landscape

GPS coordinate of the point in the plot

- 0-20 cm
- 20 – 40 cm

E.3.1.3. Sample from the bottom of the landscape

GPS coordinate of the point in the plot

- 0-20 cm
- 20 – 40 cm

Enumerator, please ensure to thank the respondents for both their time and willingness to grant you access to their field/plot.

E2. Chichewa version of the household-level questionnaire

Kuunika chomwe chasintha chifukwa chopanga ulimi oteteza chilengedwe ndikuchulukitsa zokolora (CSA) kuchigawo chakum'mwera kwa dziko la Malawi: Kulumikizitsa ulangizi wa zaulimi ku kasamalidwe ka chilengedwe ndi chakudya chokwanira

Individual household level protocol

E.1. Nambala ya boma |___|___|___|

E.1.2. Mfumu yaikulu (TA) |___|___|___||___|

E.1.3. Mfumu ya midzi ingapo (GVH) ID |___|___|___|

E.1.4. Dzina la mudzi |_________________|

E.1.5.1. Mudzi omwe munali chitukuko cha Wala = 1,

E.1.5.2. Mudzi omwe munalibe chitukuko cha Wala = 2

E.1.6. Nambala ya banja |___|___|___|

E.1.7. Tsiku lo yankha mafunso |___|___|___|

E.1.8. Numbala ya pepela lofunsira mafunso |___|___|___|

E.1.9. Nthawi yoyambira kufunsa mafunso |___________|

District codes

Balaka	= 01
Chikwawa	= 02
Nsanje	= 03
Thyolo	= 04
Zomba	= 05

EPA codes

Bazalie	= 0101
Livunzu	= 0201
Mitole	= 0202
Makhanga	= 0301
Zunde	= 0302
Massambajati	= 0401
Thekerani	= 0402
Thondwe	= 0501

Treatment GVH codes

Chicololere	= 010101
Kasisi	= 020101
Mparma	= 020201
Gatorma	= 30101
Mbangu	= 030201
Nkusa	= 040101
Gombe	= 040201
Mbeluwa	= 050101

Control GVH codes

Mpoto	= 010102
Chavala	= 020102
Nyambaru	= 020202
Alufazema	= 030102
David	= 030202
Mangwalala	= 040102
Chalonda	= 040202
Kutambala	= 050202

E.1.10. Nthawi yomalizira kufunsa mafunso |___________|

E.1.11. Dzina la ofunsa mafunso ndi nambala yake ____________________________________

Iangizo kwa ofunsa: Dziwani kuti 'dera' mmaphunzirowa, likuyimila mudzi kapena midzi ingapo (GVH) *Werengerani kalata yopempha chilorezo musanapitilile kucheza. Mulibwanji, Dzina langa ndi________, ndipo ndine ochita kafukufuku yemwe ndikuimila ophunzira yemwe akuchita maphunziro apamwamba kusukulu ya ukachenjede ya Illinois ku United States of America. Tikufuna titamvetsetsa zambili za ulimi osamalira chilengedwe ndi kuchulukitsa zokolora (CSA) mu dera lanu lino. Ife sitikugwila ntchito ndi bungwe lina lililose, boma kapena chipani china chilichonse. Cholinga chathu, tikufuna timvetsetse zomwe alimi ngati inu mumachita pa ndondomeko zosiyanasiyana zili pansi pa ulimi osamalira chilengedwe ndikuchulukitsa zokolola (CSA). Choncho ndikufuna nditacheza ndi amene amapanga ziganizo pa mkhani za ulimi pa nyumba panu pano.*

A12. Dzina la woyankha mafuso ____

E.1.**1. Kuunika maganizo a banja pa zokhudza ndondomeko ya ulimi oteteza chilengedwe ndikuchulukitsa zokolola (CSA)**

Funso	**Yankho**	**Funso**	**Yankho**
1. Zaka zawo, mopenekela (kwa ofunsa: dziwani kuti oyankha mafunso sakuyenela kuchita kunena zaka zawo zenizeni)	• 18 – 25 =1 • 26 – 35 =2 • 36 – 45 =3 • 45 – 60 = 4 • Zaka zoposela 60 =5	2. Kodi banja lanu mwakhala nthawi yaitali bwanji mdera lino?	i. Zaka zosaposela ziwiri ( ), **Siyani kucheza naye.** ii. Zaka 2 – 5 ( ) iii. Zaka 5-10 ( ) iv. Zaka zopitilira 10 ( )
3. Chimene chimapezetsa ndalama pakhomo ndi chani?	Ulimi = 1 Pali zina? = 0, tchulani ………. ……………………………... ……………………………...	4. Kodi m'banjamu ndinu ndani?	Mutu wa banja = 1 Mwamuna/mkazi = 2 Mwana wa mamuna = 3, Mwana wa mkazi = 4 wina (fotokozera)…………………..

5. Ndinu okwatira/okwatiwa?	Okwatiwa/okwatiwa = 1, Zina = 0	6. Maphunziro anu munalekezela pati?	i. Yunivesite = 1 ii. Sekondale = 2 iii. Pulayimale = 3 iv. Simunapiteko ku sukulu = 4
7. Kodi m'banja mwanu muno mulipo anthu angati nonse?	<u>Anthu</u> <u>Nambala</u> i. Amuna = ii. Akazi = iii. Ana =	8. Kodi ndi anthu angati m'banjali omwe ali ku: - sukulu ya pulayimale - ya sekondale - yantchito za manja - ku yunivesite	Nambala ya anthu
9. Kodi chimene mumadalila kwambili pakhomo pano chomwe chimakubweletselani ndalama ndichani?	i. Ulimi wa mbeu okha = 1 ***(dumphani funso. 34 – 36)*** ii.Ulimi wa ziweto zokha = 2 ***(dumphani mpakana funso 34***). iii. Ulimi wa mbeu ndi ziweto = 3 iv. Zina (tchulani)………… ………………………………..	10. Ngati ndi ulimi wa mbeu zokha, ndi mbeu zanji zomwe mumakonda kulima pa chaka (nyengo iliyonse ya mvula) Onani ma code a mbewu	Lowetsani ma code
11. Kodi ndi munda/minda ingati yomwe muli nayo?	Tchulani makulidwe	12. Pa malo onse olima omwe muli nawo, ndi minda ingati imene mumakonda kulima?	Ikani nambala
13. Nanga ndi minda ingati yomwe munalima chaka chino (2016)?	Tchulani makulidwe a mindayo.	14. Kodi ndi mbeu zanji zomwe munalima chaka chino pa minda yanu (2016)?	Lowetsani ma manambala a mbeu
15. Tingati, Munda wanu onse kapena minda ing'onoing'ono ndiyaikulu/waukulu bwanji??	i. ochepela ekala imodzi = 1 ii. 1.5 – 5 ekala = 2 iii. 5 – 10 ekala = 3 iv.oposela 10 ekala = 4	16. Kodi paminda yanu yonse yomwe muli nayo, pali wina omwe uli potsetseleka?	Eya = 1 Ayi = 0, dumphani mpakana 20.

<table>
<tr><td>17.Paminda muli nayoyo, kodi ndi minda ingati yomwe ili yotsetseleka motele:
- otsetseleka kwambili
- otsetseleka pang’ono
- osatsetseleka (fulati)</td><td>
<u># yaminda</u> <u>Makulidwe</u></td><td>18. Kodi mukuganiza kuti kulima malo otsetseleka kuli ndi vuto lililonse?</td><td>Eya = 1
Ayi = 0, dumphani mpakana 20.</td></tr>
<tr><td>19. Ndi vuto/mavuto anji?</td><td>i. zimafuna ogwila ntchito ambili ( )
ii. Kusowa kwa madzi mu nthaka ( )
iii. kusowa kwa chonde mu nthaka ( )
iv. Zina (tchulani) …………
………………………….</td><td>20. Tchulani nambala ya minda imene munalima mu zaka 5 zapitizi ndimakulidwe ake mma ekala
- 2011
- 2012
- 2013
- 2014
- 2015</td><td>
<u># ya minda</u> <u>makulinde (mma acres)</u>
______ ______
______ ______
______ ______
______ ______
______ ______</td></tr>
<tr><td>21.Kodi mumatsatila njira zanji za ulimi pa minda nanu?
i. kulima mbeu imodzi yokha pamunda umodzi
ii. Kulima mbeu zosiyanasiyana pamunda umodzi
iii. Zina (tchulani)……….……………
……………………………..
……………………………..</td><td><u>Eya = 1, tchulani</u> <u>Ayi = 0</u></td><td>22. Muzaka 5 zapitazo tchulani mbeu zomwe munalima mminda yanu ndi kukula kwa mindayo.
- 2011
- 2012
- 2013
- 2014
- 2015</td><td>Onani ma manambala (kodi) a mbeu
<u>Mbeu</u> <u>Makulidwe a munda</u>

______ ____________
______ ____________
______ ____________
______ ____________
______ ____________</td></tr>
</table>

23. Muzaka 5 zapitazo, kodi chonde mu nthaka ya munda/minda yanu chinali chotani? - 2011 - 2012 - 2013 - 2014 - 2015	Opanda Wachonde Wachonde chonde kwambili (1) (2) (3) ______ ______ ______ ______ ______ ______ ______ ______ ______ ______ ______ ______ ______ ______ ______	24. Mongoganizila, kodi mukuona ngati chonde cha mminda yanu chasintha pa zaka 5 zapitazi (2011 to 2015)?	Munda Eya =1 Ayi = 0
25. Ngati chonde chinasintha, kodi kusinthako kunali kwa ubwino kapena ayi?	Kwa ubwino = 1 Osati kwa ubwino = 0, dumphani mpaka 30.	26. Kodi ndikusintha kwa ubwino kwanji komwe kunachitika?	i. Chonde mu nthaka chidaonjezeleka ( ) ii. Madzi amalowa bwino mu nthaka ( ) iii. Chinyotho chochuluka mu nthaka ( ) iv. Kuchuluka kwa mbeu zotchinga nthaka ( )
27. Mkaganizidwe kanu, mukuona kuti ndichiyani kwekweni chidapangitsa kusintha kumeneku?	i. Njira zabwino zakasamalidwe ka nthaka ( ) ii. Chidwi chambili poteteza nthaka kuti isakokoloke ( ) iii. Chidwi chochuluka podzala mbeu zotchinga nthaka ( ) iv. Zina (tchulani)………… ………………………………	28. Kodi pa minda/munda wanu, munachitako za kasamalidwe ka madzi ndi nthaka?	Eya = 1 Ayi = 0

29. Nanga ndi njira zanji za kasamalidwe ka nthaka zimene inu kapena munthu aliyense mukumudziwa anatsatira pa munda/mindayi (2011 – 2015)?	i. Kudzala mbeu zotchinga nthaka ( ) ii Njira zotchingila madzi ( ) iii. Kudzala mitengo ( ) Iv. Zina (tchulani) ………… ………………………….	30. Kodi pa zaka 5 zapitazi, ndizosintha zanji zolakwika zomwe zinachitika pa minda yanu (2011– 2015)?	i. Kuguga kwa nthaka chifukwa chakukokoloka kwa nthaka ( ) ii. Kutha kwa chonde mu nthaka ( ) iii. Kusoweka kwa chinyotho mu nthaka kuti mbeu zikule bwin ( ) iv. Zina (tchulani) …………….. ………………………………
31. Mu zaka 5 zapitazi, kodi banja lanu lidalembako antchito ena othandizila kumunda?	Eya = 1 Ayi = 0, dumphani mpaka 33.	32. Mu zaka 5 zapitazi, (nthawi ya mvula) kodi ndi ndalama zokwanila zingati zomwe mudagwiritsa ntchito pa izi? - Kudzala - Kupalira - Kukolola Zina (tchulani)…	Tchulani ndalama yonse yomwe inagwiritsidwa ntchito pa ekala, pa nthawi yonse yolima, ndi chaka. <u>Chaka</u> <u>No ya minda</u> <u>mtengo/ndalama</u>
33. Muzaka 5 zapitazo, ngati simunalembe wina aliyese okuthandizani pantchito ya ulimiyo, mukuganiza kuti mukanakhala mutagwiritsa ntchito ndalama zingati pa izi? - Kubzala - Kupalila - Kukolola - Zina (tchulani)……………. ………………………………	Mtengo pa ekla, munda, chaka. <u># ya minda</u>, <u>Chaka</u> <u>Mtengo</u>	34. Kodi ziweto zonse zomwe muli nazo ndizingati, ndipo mwakhala nzazo kwa nthawi yaitali bwanji? Zitchuleni zonse. *ofunsa:* *(1) Zindikilani tanthauzo la ziweto zake.* *(2). Dumphani funso. 26 – 33, ngati yankho pa funso 9 linali“1” mbeu zokha.*	Fotokozani motere: <u>Chiweto</u> <u>Kuchuluka</u> <u>Dzaka</u>

35. Kodi ndi ndalama zochuluka bwanji zomwe mumagwilitsa ntchito pa ziweto zanu zonse pa mwezi, kapena pa chaka	Nyengo ya chaka Chaka Mtengo Chiweto	36. Kodi ndi njira zanji za ulimi zomwe mumatsira pakusunga ziweto zanu?	Mayankho: i. Kutsekulira ziweto kuti zizikadya mwazokha = 1 ii. Kuzimangilira kuti zizidya malo amodzimodzi = 2 iii. Kuzisunga mokhola =3 iv. Zina (tchulani) ……………… ……………..
37. Pa zaka zitatu ndi zisanu zapitazi, kodi banja lanu linagwilitsa ntchito ndalama zochuluka bwanji pa zinthu izi? - Zakudya = 1 - Pa za umuyo = 2 - Pa maphunziro = 3 - Pa zaulimi = 4 - Pamayendedwe = 5 - Zina (tchulani) ……………	Ikani nambala ya zochitikazo ndi ndama zake mmusimu Zochitika, Mwezi/Telemu Chaka	38. Kodi ndalama zanu zomwe munali nazo, zimakwaniritsa zinthu izi? - Zakudya = 1 - Pa za umuyo = 2 - Pa maphunziro = 3 - Pa zaulimi = 4 - Pamayendedwe = 5	Eya = 1, dumphani mpaka 41. Ayi = 0
39. Ngati sizimakwanira, ndichifukwa chani?	- kupelewela kwa ndalama chofukwa cha zokolola zochepa ( ) - Ndalama zambili zimathera pa zochitachita zosamalira nthaka ( ) - Zina (tchulani) …………... ……………………………	40. Kodi inu ndi banja lanu mtsogolo muno, ndizinthu ziti zomwe mumafuna mutachita zotukula umoyo wanu?	i. Kupeza chakudya mosavuta ( ) ii. Kukolora mbeu zochuluka ( ) iii.Kupeza madzi okumwa mosavuta ( ) iv. Zina (tchulani) ……………… ………………………………

Kuunikira za uphungu wamalimidwe			
41. Kodi mumapeza mauphungu a zaulimi pafupipafupi mu dera lanu lino?	i. Eya = 1 ii. Ayi = 2	42. Kodi uphungu umenewu mumaumva/munaumva kuti?	i. WALA = 1 ii. UBALE = 2 iii. Alangizi a boma = 3 iv. Zina (tchulani) ………… ……………......…………...
43. Kodi mdera lanu lino muli naye mlangizi wazaulimi?	Eya = 1 Ayi = 0, dumphani mpaka 49.	44. Ngati muli naye, mumakumana naye mowirikiza bwanji?	i. Tsiku lilironse = 1 ii. Sabata iliyonse = 2 iii. Pa sabata kawiri = 3 iv. Mwezi ulionse = 4 v. Pa chaka kanayi = 5 vi. pa chaka kawiri = 6
45. Ndimauphungu anji amene banja lanu limatenga kwa alangizi azaulimiwa?	i. Kabzalidwe ka mbeu =1 ii. Kagwiritsidwe ntchito ka madzi = 2 iii. kupalira = 3 iv. Kuteteza mbeu kutizilombo toononga mbeuzo = 4 v. Zina (tchulani) …………	46. Kodi mukuganiza kwanu, mauphungu omwe munamva azaulimi muzaka ziwiri zapitazo, mungawayike pa muyeso uti?	i. Osapindulitsa ( ) ii. Opindulitsa ( ) iii. Opindulitsa kwambili ( )
47. Kodi mukuganiza kwanu, mauphungu omwe munamva azaulimi muzaka zitatu zapitazo, mungawayike pa muyeso uti?	i. Osapindulitsa ( ) ii. Opindulitsa ( ) iii. Opindulitsa kwambiri ( )	48. Kodi mukuganiza kwanu, mauphungu omwe munamva azaulimi muzaka zisanu zapitazo, mungawayike pa muyeso uti?	i. Osapindulitsa ( ) ii. Opindulitsa ( ) iii. Opindulitsa kwambili ( )
49. Kodi mumalipila kena kalikonse kuti mupeze ma uphunguwa?	Eya = 1 Ayi= 0dumphani mpaka 51	50. Ngati mumalipira, ndi ndalama zingati?	Tchulani mtengo.

Kuunikira pa kudziwa ndi zochitikachitika pa nkhani ya Ulimi osamalira zachilengedwe			
51. Kodi mukudziwako za khwawa (wotashedi) liri lonse mdera lanu lino? (Kwaofunsa, chonde fotokozi tanthauzo la wotashedi kwa ofunsidwa).	Eya = 1 Ayi = 0, dumphani mpaka 55.	52. Ngati mukudziwa, kodi mumalima mozungulira mtsinjeu?	Eya= 1 Ayi = 0 dumphani
53. Kodi minda yanu inatalikirana bwanji ndi mtsinje umeneu?	Ma kilomita ochepera 1 i. 1– 3km ii. 3 – 5 km iii. ma kilomita oposera 5	54. Kuyambila chaka cha 2011 mpaka 2015, kodi panachitika chitukuko china chirichonse kumtsinjewu mderali?	Eya= 1 Ayi = 0 dumphani
55. Kodi mukudziwa njira zamakono zokhudza ulimi osamalira chilengedwe chikuchulukitsa zokolola (Ulimi osamalira nthaka)? Kwa ofunsa, yang'anani pa notsi za ulimi osamalira nthaka.	Eya = 1 Ayi = 0 dumphani mpaka 64.	56. Mukudziwa chani zokhudza ulimi osamalira chilengedwe ndi kuchulukitsa zokolola (CSA)?	Fotokozani ………………………………….. ………………………………….. …………………………………..
57. Kodi ndi liti lomwe mudamva za ulimi osamalira nthaka. koyamba?	i. Chisadafike chaka cha 2009 = ( ) ii. 2009 – 2014 = ( ) iii. Chitapitilira chaka cha 2014 = ( ) iv. Zina (tchulani) ………… …………………………..	58. Kodi mudadziwa bwanji ulimi osamalira nthaka. ?	i. WALA = 1 ii. UBALE = 2 iii. Alangizi a boma = 3 iv. Zina (tchulani)..…....……… …….…………………………..

59. Mu zaka zisanu zapitazi, Kodi munagwiritsako ntchito njira zosamalira nthaka zomwe mudamvazo mminda yanu?	Eya = 1 Ayi = 0	60. Ndi njira ziti zokhudza kusamalira nthaka zomwe munazitsatira pa ulimi wanu mu zaka zapakati pa 2009 ndi 2015?	Chongani mayankho. • Tchinga lamiyala ( ) • CCTs ( ) • WATs ( ) • Mizere yotsatila kalozera ( ) • Ulimi osakaniza ndi mitengo ( ) • Udzu wa thedzi ( ) - makanala ( ) - Zina (nthulani)………... …………………………
61. Kodi nchifukwa chani mudatsatira njira zimenezi?	- Kuchepetsa madzi othamanga = 1 - Kukolora madzi = 2 - Kuchulukitsa zokolora = 2 - Zina (tchulani) ………… ……………………………. ……………………………..	62. Kodi paminda panu mukutsatira njira iliyonse yokhudza ulimi osamalira nthaka?	Eya= 1 Ayi = 0, dumphani mpaka 64
63. Ndi njira ziti zomwe mukutsatira pakadali pano(s)?	Chongani mayankho. • Tchinga lamiyala ( ) • CCTs ( ) • WATs ( ) • Mizere yotsatila kalozera ( ) • Ulimi osakaniza ndi mitengo ( ) • Udzu wa thedzi ( ) - makanala ( ) - Zina (nthulani)………... …………………………	64. Kodi mukudziwa zimene anachita a WALA zokhudzana ndi khwawa (watershed) mdera lanu lino??	Eya =1, Ayi, dumphani mpakana 70

65. Kodi banja lanu lidathandizidwako ndi a WALA pankhani yachitukuko cha watershed?	Eya = 1 Eya = 0, dumphani mpaka 73.	66. Ndichithandizo chanji chomwe mudalandira kuchokera ku pologamu ya WALA watershed?	Tchulani zonse.
67. Mu zaka 5 zapitazi, kodi inuyo kapena wina aliyense m'banja lanu, anatengako mbali mu komiti ya WALA watershed mu dera lanu lino?	Eya = 1 Ayi = 0, dumphani mpakana 73.	68. Ngati munatengapo mbali, mumapanga zotani?	• Tchinga lamiyala ( ) • CCTs ( ) • WATs ( ) • Mizere yotsatila kalozera ( ) • Ulimi osakaniza ndi mitengo ( ) • Udzu wa thedzi ( ) - makanala ( ) - Zina (nthulani)………... …………………………
69. Mudayamba liti kupanga zinthuzi mminda yanu?	- 2011 ( ) - 2012 ( ) - 2013 ( ) - 2014 ( ) - 2015 ( )	70. Pali njira zina kupatula zatchulidzwazi zokhudza kumalira nthaka zomwe mmapanga mminda yanu zomwe panalibe chinasafike chaka cha 2014?	Eya = 1 Ayi = 0
71. Kodi pali njira zokhudza Kusamalira nthaka zomwe zinalipo munchaka cha 2014 zomwe panopa palibe?	Eya = 1 Ayi = 0	72. Ngati zilipo ndi ziti?	Tchulani

<table>
<tr>
<td>73 .Mutakhala kuti muli ndi mwayi wosankha njira zingapo zamakono zokhudza kusamalira nthaka, kodi mukuganiza kuti ndi njira ziti zimene zingabweretse zokolola zochuluka? Tchulani kuyambira njira yodalilika kwambiri.</td>
<td colspan="2">Mbeu Njira
______ ________________________________
______ ________________________________
______ ________________________________
______ ________________________________
______ ________________________________

Ofunsa, lowetsani ma nambala za mbeu kuchokela mu notsi zanu</td>
<td>Chongani njira zonse:
- Tchinga lamiyala ( )
- CCTs ( )
- WATs ( )
- Mizere yotsatila kalozera ( )
- Ulimi osakaniza ndi mitengo ( )
- Udzu wa thedzi ( )
- makanala ( )
- Zina (nthulani)………..
• …………………………</td>
</tr>
<tr>
<td>74. Chonde pelekazi zifukwa za mayankho anu.</td>
<td colspan="2">Fotokozani.</td>
<td></td>
</tr>
<tr>
<td colspan="4">Chomwe chingasinthe kumbali ya zokolola komaso mapezekedwe a madzi chifukwa chopanga ulimi osamalira chilengedwe ndi kuchulukitsa zokolola (CSA).</td>
</tr>
<tr>
<td>75. Kodi mu chaka cha 2010 munakolola matumba angati (mmatumba a 50kgs)?</td>
<td>Kuchuluka kwake</td>
<td>76. Kodi mu chaka cha 2014 munakolola matumba angati (mmatumba a 50kgs)?</td>
<td>i. 0 – 20 ( )
ii. 21 – 50 ( )
iii. 51 – 100 ( )
iv. 100 ( )</td>
</tr>
<tr>
<td>77. Kodi mu chaka cha 2015 munakolola matumba angati (mmatumba a 50kgs)?</td>
<td>Kuchuluka kwake</td>
<td>78. Kodi mu chaka cha 2016 munakolola matumba angati (mmatumba a 50kgs)?</td>
<td>i. ochepela 20 ( )
ii. 21 – 50 ( )
iii. 51 – 100 ( )
iv. 100 ( )</td>
</tr>
</table>

79. Kuyambila nchaka cha 2011 kufikila chaka cha 2015 mwaonako kusintha kwa zokolola zanu? - 2011 - 2012 - 2013 - 2014 - 2015	Mmatumba a 81 kg <u>Eya = 1 (Kuchuluka kwake)</u> <u>Eya = 0</u>	80. Mukuganiza kuti chidapangitsa kusintha kumeneku chenicheni nchiyani? -Kupezeka kwa chinyontho mu nthaka kamba ka kuchepa kwa madzi othamanga - Kuchuluka kwa madzi a mvula olowa mu nthaka - Kugwiritsa ntchito manyowa abwino - Zina (tchulani)	Eya = 1 Ayi = 0
81. Kodi munda wanu uli pafupi ndi mtsinje?	Eya = 1 Ayi = 2	82. Kodi mtsinje umeneu ndi ozama bwanji?	i. Mmapazi ( ) ii. M'mawondo ( ) iii. munchiuno ( ) iv. mmapewa ( ) v. Opitilira msinkhu wa munthu ( )
83. Kodi pakali pano, mtsinje umenewu ndiozama bwanji?	i. Mmapazi ( ) ii. M'mawondo ( ) iii. munchiuno ( ) iv. mmapewa ( ) v. Opitilira msinkhu wa munthu ( )	84. Mu nchaka cha 2015 mtsinje umenewu unali ozama bwanji?	i. Mmapazi ( ) ii. M'mawondo ( ) iii. munchiuno ( ) iv. mmapewa ( ) v. Opitilira msinkhu wa munthu ( )
85. Mu nchaka cha 2014 mtsinje umenewu unali ozama bwanji?	i. Mmapazi ( ) ii. M'mawondo ( ) iii. munchiuno ( ) iv. mmapewa ( ) v. Opitilira msinkhu wamunthu ( )	86. Mu nchaka cha 2013 mtsinje umenewu unali ozama bwanji?	i. Mmapazi ( ) ii. M'mawondo ( ) iii. munchiuno ( ) iv. mmapewa ( ) v. Opitilira msinkhu wa munthu ( )

87. Muzaka zapakati pa 2009 ndi 2012 mtsinje umenewu unali ozama bwanji?	i. Mmapazi ( ) ii. M'mawondo ( ) iii. munchiuno ( ) iv. mmapewa ( ) v. Opitilira msinkhu wamunthu ( )	88. Kodi Munaonako kusintha kulikonse pakachulukidwe ka madzi ogwiritsa ntchito pakhomo panu chiyambileni kutenga nawo mbali pa zochitikachitika zosamalira ndondomeko zokhudza makhwawa (watershed) zomwe adakhazikitsa a WALA?	Eya = 1 Ayi = 0
89. Kodi inu ndi banja anu mwaona kusintha kwanji pakupezeka kwa madzi ndikachulukidwe kwake?	Tchulani zones	90. Mukuona ngati ndi chiyani chachititsa kusintha kumeneku?	Tchulani zonse.
Chomwe chingachitike/chingasinthe kumbali ya mapezedwe a chakudya chokwanira			
91. Kodi mumadziwa za nkhani yokhala ndi chakudya chokwanira?	Eya = 1, Ayi = 0	92. Nanga mukudziwa chani za nkhani yokhala ndi chakudya chokwanira?	Tchulani mayankho onse.
93. Mu zaka za m'mbuyozi tisadafike 2015, kodi mumakwanitsa kukhala ndi chakudya chokwanira?	Yes = 1, No = 0	94. Chisadafike chaka cha 2014, ndi ziti mwa zakudya izi zimene banja lanu limadya pa sabata? - Chimanga - zamasamba ndi zipatso - Shuga - zamafuta - Nsomba - Zanyama - Zina (tchulani)…………… ……………………………..	Penekelani

95. Mu chaka cha 2015, ndi ziti za mwa zakudya izi zimene banja lanu limadya pa sabata? - Chimanga - zamasamba ndi zipatso - Shuga - zamafuta - Nsomba - Zanyama - Zina (tchulani)…………… ……………………………..	Penekerani	96. Kuchokera nchaka cha 2016, ndi ziti za mwa zakudya izi zimene banja lanu limadya pa sabata? - Chimanga - zamasamba ndi zipatso - Shuga - zamafuta - Nsomba - Zanyama - Zina (tchulani)…………… ……………………………..	Penekelani
97. Mu nchaka cha 2014, ndalama zonse zomwe mumagwiritsa ntchito pa sabata pa zinthu izi ndi zingati? - Chimanga - zamasamba ndi zipatso - Shuga - zamafuta - Nsomba - Zanyama - Zina (tchulani)…………… ……………………………..	Penekelani	98. Mu nchaka cha 2015, ndalama zonse zomwe mumagwiritsa ntchito pa sabata pa zinthu izi ndi zingati? - Chimanga - zamasamba ndi zipatso - Shuga - zamafuta - Nsomba - Zanyama - Zina (tchulani)…………… ……………………………..	Penekelani

99. Mu nchaka cha 2016, ndalama zonse zomwe mumagwiritsa ntchito pa sabata pa zinthu izi ndi zingati? - Chimanga - zamasamba ndi zipatso - Shuga - zamafuta - Nsomba - Zanyama - Zina (tchulani)…………… ……………………………..	Penekelani	100. Kuyambila chaka cha 2016 pabata mumagula ndi ndalama zingati zadya izi: - Chimanga - Zipatso ndi ndiwo zakudimba - Shunga - Mafuta ophikira - Nsomba - Nyama - Zina (Fotokozani)……… ……………………………..	Penekelani
101. Muzaka ziwiri zanjala zomwe zapitazi, mumagwiritsa ntchito ndalama zochuluka bwanji pamwezi pogulira: - Chimanga - Masamba ndi zipatso - Shuga - zamafuta - Nsomba - Zanyama - Zina (tchulani)…………… ……………………………..	Penekelani	102. Kuyambira nthawi yomwe tikumana ndikuchepa kwa mchaka chino pa mwezi mumagwiritsa ntchito ndalama zingati pogula: - Chimanga - Zipatso ndi ndiwo zakudimba - Shunga - Mafuta ophikira - Nsomba - Nyama - Zina (Fotokozani)……… ……………………………..	Penekelani

103. Kodi inuyo, kapena aliyense wapakhomo pano, mukuona ngati simukhala ndi chakudya chokwanira pamasiku awiri akubwerawa?	Eya = 1, Ayi = 0	104. Kodi inuyo, kapena aliyense wapakhomo pano, mukuona ngati simukhala ndi chakudya chokwanira cha tsiku ndi tsiku sabata ikubwerayi?	Eya = 1, Ayi = 0
105. Kodi inuyo, kapena aliyense wapakhomo pano, mukuona ngati simukhala ndi chakudya chokwanira cha tsiku ndi tsiku m'mwezi ukubwerawu?	Eya = 1, Ayi = 0	106. Kodi inuyo, kapena aliyense wapakhomo pano, mukuona ngati simukhala ndi chakudya chokwanira cha tsiku ndi tsiku m'miyezi itatu ikubwerayi?	Eya = 1, Ayi = 0
Kuyesa masowedwe a chakudya pakhomo			
107. Masiku 30 apitawa, inu kapena wina aliyense wapakhomo pano, anadandaulako kuti simukhala ndi chakudya chokwanira?	Eya = 1, Ayi = 0	108. Masiku 30 apitawa, inu kapena wina aliyense wapakhomo pano, munalepherako kudya chakudya chomwe mumafuna kamba kosowa chuma?	Eya = 1, Ayi = 0
109. Masiku 30 apitawa, inu kapena wina aliyense wapakhomo pano, anadyako zakudya zamagulu ochepa tsiku ndi tsiku kamba kosowa chuma?	Eya = 1, Ayi = 0	110. Masiku 30 apitawa, inu kapena wina aliyense wapakhomo pano, munadya zakudya zomwe simumafuna kamba kosowa chuma?	Eya = 1, Ayi = 0

111. Masiku 30 apitawa, inu kapena wina aliyense wapakhomo pano, munadyako chakudya chochepa chifukwa munalibe chakudya chokwanira?	Eya = 1, Ayi = 0	112. Masiku 30 apitawa, inu kapena wina aliyense wapakhomo pano, munadumphitsako chakudya china chomwe mumayenera kudya patsiku chifukwa munalibe chakudya chokwanira?	Eya = 1, Ayi = 0
113. Masiku 30 apitawa, inu kapena wina aliyense wapakhomo pano, anagonako ndi njala chifukwa panalibe chakudya chokwanira?	Eya = 1, Ayi = 0	114. Masiku 30 apitawa, inu kapena wina aliyense wapakhomo pano, anakhalako tsiku lonse osadya chifukwa panalibe chakudya chokwanira?	Eya = 1, Ayi = 0
115. Masiku 30 apitawa, kodi panalibiretu chakudya pakhomo panu chifukwa chakusowa zothandizira kupeza zina?	Eya = 1, Ayi = 0	116. Nanga masiku 7 apitawa, munadandaulako kuti inuyo kapena wina aliyense wapakhomo panu simukhala ndi chakudya chokwanira?	Eya = 1, Ayi = 0
117. Masiku 7 apitawa, inu kapena wina aliyense wapakhomo pano, munalepherako kudya chakudya chomwe mumafuna kamba kosowa chuma?	Eya = 1, Ayi = 0	118. Masiku 7 apitawa, inu kapena wina aliyense wapakhomo pano, munadyako zakudya zamagulu ochepa tsiku ndi tsiku chifukwa chakusowa chuma?	Eya = 1, Ayi = 0
119. Masiku 7 apitawa, inu kapena wina aliyense wapakhomo panu, munadyako chakudya chomwe simumafuna kudya chifukwa chakusowa chuma?	Eya = 1, Ayi = 0	120. Masiku 7 apitawo, inu kapena wina aliyense wapakhomo pano, munadyako chakudya chochepa chifukwa chakusowa chuma?	Eya = 1, Ayi = 0

121. Masiku 7 apitawa, inu kapena wina aliyense wapakhomo pano, munadyako chakudya chochepa chifukwa chakusowa chuma?	Eya = 1, Ayi = 0	122. Masiku 7 apitawa, inu kapena wina aliyense wapakhomo pano, munadumphitsako chakudya china chomwe mumayenera kudya patsiku chifukwa munalibe chakudya chokwanira?	Eya = 1, Ayi = 0
123. Masiku 7 apitawa, inu kapena wina aliyense wapakhomo panu, anakhalako tsiku lonse osadya chifukwa panalibe chakudya chokwanira?	Eya = 1, Ayi = 0	124. Masiku 7 apitawa, kodi panalibiretu chakudya pakhomo panu chifukwa chakusowa zothandizira kupeza zina?	Eya = 1, Ayi = 0
125. Maola 24 apitawa, inu kapena wina aliyense wapakhomo panu mukhalako opanda chakudya chokwanira?	Eya = 1, Ayi = 0	126. Maola 24 apitawa, inu kapena wina aliyense wapakhomo panu, munadyako chakudya chomwe simumafuna kudya chifukwa chakusowa chuma?	Eya = 1, Ayi = 0
127. Maola 24 apitawa, inu kapena wina aliyense wapakhomo panu, munadyako zakudya zamagulu ochepa tsiku ndi tsiku chifukwa chakusowa chuma?	Eya = 1, Ayi = 0	128. Maola 24 apitawa, inu kapena wina aliyense wapakhomo panu, munadyako chakudya chomwe simumafuna kudya chifukwa chakusowa chuma?	Eya = 1, Ayi = 0

129. Maola 24 apitawa, inu kapena wina aliyense wapakhomo pano, munadyako chakudya chochepa chifukwa chakusowa chuma?	Yes = 1, No = 0	130. Maola 24 apitawa, inu kapena wina aliyense wapakhomo pano, munadyako chakudya chochepa chifukwa chakusowa chuma?	Yes = 1, No = 0
131. Maola 24 apitawa, inu kapena wina aliyense wapakhomo pano, anagonako ndi njala chifukwa panalibe chakudya chokwanira?	Yes = 1, No = 0	132. Maola 24 apitawa, nu kapena wina aliyense wapakhomo pano, anakhalako tsiku lonse osadya chifukwa panalibe chakudya chokwanira?	Yes = 1, No = 0
133. Maola 24 apitawa, kodi panalibiretu chakudya pakhomo panu chifukwa chakusowa zothandizira kupeza zina?	Yes = 1, No = 0	134. Maola 24 apitawa, kodi mwagwiritsa ntchito ndalama zingati pa zinthu izi: - Chimanga - Zipatso ndi masamba - Shuga - Zamafuta - Zansomba - Zanyama	Penekelani

135. Masiku 7 apitawa, kodi mwagwiritsa ntchito ndalama zingati pa zinthu izi: - Chimanga - Zipatso ndi masamba - Shuga - Zamafuta - Zansomba - Zanyama	Penekelani	136. Masiku 30 apitawa, kodi mwagwiritsa ntchito ndalama zingati pa zinthu izi: - Chimanga - Zipatso ndi masamba - Shuga - Zamafuta - Zansomba - Zanyama	Penekelani

Section E2: Kuunika chonde mu nthaka
Langizo
Ufunsa nenani kwa ofunsidwa kuti: Ndimafuna kuyendela munda/minda yanu kuti tikatapeko dothi ndicholinga choti tikalipime. Choncho tikupemphani kuti mutipelekeze ku munda omwe mwakhaIa mukulima mu zaka 5 zapitazi.

- Eya = 1, Ngati avomera, pitilizani kukatenga dothilo.
- Ayi = 0, siyani kucheza nawo.

E2.1. GPS coordinate of the plot
- Latitude
- Longitude

E2.2. Maonekedwe/kuwufotoza munda
- Mtunda kuchokera kumudzi ______________________________________
- Nambala ya munda/minda _______________
- Mtunda kuchokela pa khwawa (watershed) loyandikira yomwe ili lokonzedwa =
- Mtunda kuchokera pa khwawa (watershed) loyandikira lomwe lili yosakonzedwa =
- Munda wanu unalimidwa mchaka cha 2015? Eya =1, Ayi = 0
- Ngati unalimidwa, munalimamo mbeu zanji? ____
- Kuchokera muzaka za pakati pa 2011-2015, mumatsatira ndondomeko yanji yakalimidwe ka mbeu?

E.2.3. **Onani ndi maso**: Kodi mukuonako maupangiri an ulimi wosamalira chilengedwe ndikuchulukitsa zokolora (CSA) pamundawu?

Funso	**Yankho**	**Funso**	**Yankho**
Maupangiri a ulimi osamalira chilengedwe ndikuchulukitsa zokolora (CSA)	Eya =1 Ayi = 2	Ngati alipo, ziripo zingati?	M'mene ziriri: Zogwira bwino ntchito = 1 Zowonongeka = 2
Masuwale(WAT)			
milambala (CCT)			
akalozera			
Tchingo ya miyala			
Ulimi sokaniza ndi mitengo			
Thedzi			
makanala			

E.2.3. Ndondomeko ya katengedwe ka dothi pamunda: Mukafika pamunda tengani dothi motere:

E.2.1. Tengani dothi la kumtunda kwa munda
GPS coordinate of the point in the plot

- Latitude
- Longitude
- 0-20 cm
- 20-40 cm

E.2..1.2. Tengani dothi lapakati pa munda
GPS coordinate of the point in the plot

- 0-20 cm
- 20-40 cm

E2.1.3. Tengani dothi la kumunsi kwa munda
GPS coordinate of the point in the plot

- 0-20 cm
- 20-40 cm

Wofunsa, kumbukirani kumuthokoza woyankha chifukwa cha nthawi yake komanso kulola kutenga dothi m'munda mwawo.

APPENDIX F:

KEY INFORMANT INTERVIEW GUIDE IN ENGLIGH AND CHICHEWA

F1. English version of the key informant interview guide

An Ex-Post Impact Evaluation of the Adoption of Climate Smart Agriculture in Southern Malawi: Linking Agricultural Extension to Environmental Conservation and Food Security

Community level protocol: Key Informant Interview

F.1.1. District code |___|___|

F.1.2. Group Village Head (GVH) ID |___|___|___|

F.1.3. Community name or ID |_________________|

F.1.4. Community type (Treatment = 1, Control = 2)

F.1.5. Interview date |___|___|___|

F.1.6. Questionnaire number |___|___|___|

F.1.7. Time interview started |___________|

F.1.8. Time interview ended |___________|

F.1.9. Interviewer name and ID _______________|

District codes

Balaka	= 01
Chikwawa	= 02
Nsanje	= 03
Thyolo	= 04
Zomba	= 05

EPA codes

Bazalie	= 0101
Livunzu	= 0201
Mitole	= 0202
Makhanga	= 0301
Zunde	= 0302
Massambajati	= 0401
Thekerani	= 0402
Thondwe	= 0501

Treatment GVH codes

Chicololere	= 010101
Kasisi	= 020101
Mparma	= 020201
Gatorma	= 030101
Mbangu	= 030201
Nkusa	= 040101
Gombe	= 040201

Control GVH codes

Mpoto	= 010102
Chavala	= 020102
Nyambaru	= 020202
Alufazema	= 030102
David	= 030202
Mangwalala	= 040102
Chalonda	= 040202
Kutambala	= 050202

Instruction to Enumerator: Note that in this study, the term *COMMUNITY* refers to village or group of villages (GVH).

Before the interview, please use the following script to obtain a consent for interview.

Hello. My name is ____, and I am a research assistant for a doctoral dissertation research conducted by a PhD student from University of Illinois at Urbana-Champaign. We are interested in understanding the effects of climate smart agriculture (CSA) in this community. We do not represent any government agency or NGO in Malawi, or any political party. We want to understand your experiences regarding climate smart agriculture in this community. I would like to speak to you as a key informant regarding agricultural practices and environmental conservation in this community.

Then read the oral consent letter to respondent in order to obtain oral consent before proceeding with the interview.

F.1.1. Assessment of community perception of climate smart agriculture (CSA) practices

Question	Response	Question	Response
1. Respondent's name or pseudo-name	………………………..	2. Gender	i. Male = 1 ii. Female = 0
3. Approximate age	Estimate	4. Respondent's main role in the community: i. Headman =1 ii. Counselor =2 iii. School teacher =3 iv. Religious leader=4 v. Health worker=5 vi. Agricultural field worker (extension agent) =6 vii. Lead farmer =8 viii. Others = 9 (specify)………….. ………………………………..	Indicate

5. Approximately, how many households live in this community?	i. Less than 20 ( ) ii. 21-50 ( ) iii. 51 – 70 ( ) iv. 71 – 100 ( ) v. Above 100 ( )	6. What is the main source of livelihood support for this community?	Cropping = 1 Livestock rearing = 2 Other (specify)…………...... …………………………..
7. Approximately what proportion of households in this community: - Grow crops = 1 - Raise livestock = 2 - Both crops & livestock = 3	i. One in ten ( ) ii. Three in ten ( ) iii. Five in ten ( ) iv. Seven in ten ( ) v. All (100%) ( )	8. What is/are the major crop(s) grown in this community?	Enumerator, refer to your note and enter crop code(s) here. Enter crop code(s) here.
9. What are the main animals raised in this community?	i. Cattle ( ) ii. Chicken/poultry ( ) iii. Goat ( ) iv. Pigs ( ) v. Other (specify)……. ..…………………….	10. How are animals usually raised in this community?	Response: i. Free range = 1 ii. Controlled grazing in restricted areas = 2 iii. Intensive = 3 iv. Other (specify) ………… ……………...........................
11. In a typical rainy season, how usually is the weather pattern in this community? - Usually very dry = 1 - Moderately = 2 - Wet = 3 - Very wet = 4	Enter codes here	12. What is the main landscape in this community? - Predominantly flat = 1 - Somewhat flat = 2 - Predominantly hilly = 3 - Somewhat hilly = 4	Enter codes here
13. Does this community have any watershed(s)?	Yes = 1 No = 0, skip to 24	14. If yes, how many watershed are there in this community?	i. 1- 3 ( ) ii. 3- 5 ( ) iii. More than 5 ( )

15. What is the average distance to the nearest watershed from the community center?	i. Less than 1km = 1 ii. 1 to 5 km = 2 iii. 5 to 10km = 3	16. What proportion of farmers in this community cultivate in, or around the watershed?	i. One in ten ( ) ii. Three in ten ( ) iii. Five in ten ( ) iv. Seven in ten ( ) v. All (100%) ( )
17. Over the past five years (2011-2015), were there any visible changes to the watershed(s) in this community?	Yes = 1 No = 0, If No, skip to 20.	18. If yes, what are the major changes to the watershed (s)?	Explain
19. What do you think is responsible for the change(s)?	Outline	20. Over the past five years, has any of these watersheds been developed?	Yes = 1 No = 0, skip to 24.
21. If yes, which kind(s) of development did the watershed(s) receive?	1. Continuous contours (CCTs) 2. Water absorption trenches (WATs) 3. Maker ridges 4. Vetiver grass 5. Agroforestry 6. Other (specify) ………………......	22. Did your community receive any support in developing these watershed?	Yes = 1 No = 0 Skip to 24
23. Which organization or project supported the watershed development?	Name	24. Is there an irrigation scheme in this community?	Yes = 1 No = 0, If No, skip 26.
25. What is the source of the irrigation scheme in the community?	i. Ministry of agric. ii. NGO (specify)…….. …..………………... iii. Other (specify) …... ..…………............	26. Is there an agricultural extension worker in this community?	Yes = 1 No = 0, skip to 31.

27. If yes, what is the distance to the nearest agricultural extension worker(s) from this community?	Distance in km: i. Below = 1 ii. 1 to 2 = 2 iii. 2 to 5 = 3 iv. More than 5 = 4	28. On average, how often do farmers in this community receive support from agricultural extension worker(s)?	i. Very frequent ( ) ii. Frequent ( ) iii. Sometimes ( ) iv. Not regular ( )
29. What main support does your community receive from the extension worker (s)?	i. Cropping ii. Water management iii. Weeding iv. Pest control v. Veterinary vi. Other (specify) …………………..	30. Overall, how do you rate the services from the extension worker(s) in this community?	i. Excellent ( ) ii. Very good ( ) iii. Good ( ) iv. Fair ( ) v. Not good ( )
31. Over the past five years (2011-2015), has there been any changes in how your community practice farming?	Yes = 1 No = 0 , If no, skip 33	32. What major changes did your community experience about farming?	i. Shorter cropping cycles ( ) ii. Longer cropping cycles ( ) iii. extremely long cycles ( )
33. Does this community know about CSA techniques?	Yes = 1 No = 0, If No, skip 35	34. How did you learn about CSA?	WALA = 1 Other = 0
35. Did your community have WALA's watershed treatment program?	Yes = 1 No = 0	36. Which kinds of watershed treatment did your community receive from the WALA program?	1. CCTs ( ) 2. WATs ( ) 3. Maker ridges ( ) 4. Vetiver grass ( ) 5. Agroforestry ( ) 6. Other (specify) ………….. ………………………......

37. Over the past five years <u>(2011-2015)</u> since 2009, what proportion of farmers have constructed watershed treatment structures, or CSA on their farms?	i. One in ten = ( ) ii. Three in ten = ( ) iii. Five in ten = ( ) iv. Seven in ten = ( ) v. All (100%) = ( )	38. What proportion of farmers in this community have the following CSA practices on their farms? 1. CCTs 2. WATs 3. Maker ridges 4. Vetiver grass 5. Agroforestry 6. Other (specify)	i. One in ten ( ) ii. Three in ten ( ) iii. Five in ten ( ) iv. Seven in ten ( ) v. All (100%) ( )
39. How did your community members learn about CSA practices on their farms?	i. From directly participating in WALA's community watershed dev't. ii. Learning from neighbors. iii. through another project/NGO (specify)	40. In general, is CSA a popular idea in this community?	Yes = 1 No = 0
41. Has there been any noticeable effects of CSA on this community?	Yes = 1 No = 0, If No, skip 43.	42. If yes, what are the main effects of CSA?	Less runoff = 1 Higher yield = 2 Other = 0
43. Over the past five years (2011-2015), did farmers in this community experience any change(s) in maize yield?	Yes = 1 No = 0	44. Over the past two years (2013-2014), did farmers in this community experience any change(s) in maize yield?	Yes = 1 No = 0
45. In the past five years (2011-2015 growing season), what was the average maize yield (in 50kg bags) per hectare in this community?	i. 0 to 10 ( ) ii. 11 to 20 ( ) iii. More than 20 ( )	46 In the past three years (2012/2013 growing season), what was the average maize yield (in 50kg bags) per hectare in this community?	i. 0 to 10 ( ) ii. 11 to 20 ( ) iii. More than 20 ( )

47. In the past two years (2013/2014 growing season) what was the average maize yield (in 50kg bags) per hectare in this community?	i. 0 to 10 ( ) ii. 11 to 20 ( ) iii. More than 20 ( )	48. In the past year (2014 growing season), what was the average maize yield (in 50kg bags) per hectare in this community?	i. 0 to 10 ( ) ii. 11 to 20 ( ) iii. More than 20 ( )
49. From the start of WALA project in 2009 to date, has there been any general improvement on soils in this community?	Yes = 1 No = 0, If No, skip 51.	50. If yes, what general improvements do you have on the soils in this community?	i. Higher water tables due to reduced run-off ii. Increased percolation of rainwater iii. Better organic matter on soil surfaces iv. Other (specify) ………………
51. Over the past two years (2013/2014), has there been any change(s) in socio-economic status for farmers in this community?	Yes = 1 No = 0, skip to 55	52. If yes, what major socio-economic changes did farmers in your community experience on average?	i. higher incomes from farming ( ) ii. higher amount of food iii. better health ( ) iv. Higher school enrollment ( ) v. Other (specify)………….. …………………………..
53. What proportion of farmers/community members have experienced positive socioeconomic changes since 2014?	i. One in ten = ( ) ii. Three in ten = ( ) iii. Five in ten = ( ) iv. Seven in ten = ( ) v. All (100%) = ( )	54. What proportion of farmers/community members have not experienced positive socioeconomic changes since 2014?	i. One in ten ( ) ii. Three in ten ( ) iii. Five in ten = ( ) iv. Seven in ten = ( ) v. All (100%) = ( )
55. For those who have not experienced positive changes, what is the possible reason for the lack of socio-economic improvement in this community?	1. El Nino effect 2. Low level of disaster preparedness 3. Health burden 4. Other (specify)……………… ………………………..	56. Which other important factors do you consider important for agriculture and socio-economic wellbeing in this community?	i. The landscape ii. Distance from urban areas iii. community health iv. Other (specify)…………………… ……………………………..

57. In the past five years, since 2011, did your community receive any training on disaster preparedness (such as environmental shocks) and CSA?	Yes = 1 No = 0, skip to 61.	58. If yes, which kind(s) of disaster preparedness training does your community have?	List.
59. Which organization provided the disaster preparedness training for this community?	Name	60. How would you rate the level of training received on disaster preparedness and CSA?	i. Very adequate ii. Somewhat adequate iii. Inadequate
61. Is there a river or stream in this community?	Yes = 1 No = 0	62. Please list the number of rivers or streams in this community.	<u># of River(s)</u> <u># of Streams</u>
63. Usually, how deep is/are the river(s) or stream(s)	i. Ankle level ( ) ii. Knee level ( ) iii. Waist level ( ) iv. shoulder level ( ) v. Beyond normal height ( )	64. What is the current depth of the river/stream?	i. Ankle level ( ) ii. Knee level ( ) iii. Waist level ( ) iv. Shoulder level ( ) v. Beyond normal height ( )
65. What was the depth of the river in 2015?	i. Ankle level ( ) ii. Knee level ( ) iii. Waist level ( ) iv. shoulder level ( ) v. Beyond normal height ( )	66. What was the depth of river in 2014?	i. Ankle level ( ) ii. Knee level ( ) iii. Waist level ( ) iv. shoulder level ( ) v. Beyond normal height ( )
67. What was the depth of the river in 2013?	i. Ankle level ( ) ii. Knee level ( ) iii. Waist level ( ) iv. Shoulder level ( ) v. Beyond normal height ( )	68. What was the depth of river between 2009-2012?	i. Ankle level ( ) ii. Knee level ( ) iii. Waist level ( ) iv. Shoulder level ( ) v. Beyond normal height ( )

69. Have you experienced any noticeable change(s) in the level of available water for your community since you started participating in the WALA watershed management?	Yes = 1 No = 0	70. What changes have you experienced?	Explain
71. What do you think is the main reason for this change?	Explain	72. What proportion of community members have easier access to safe drinking water since 2014?	i. One in ten = ( ) ii. Three in ten = ( ) iii. Five in ten = ( ) iv. Seven in ten = ( ) v. All (100%) = ( )
73. Give reason for your answer above	Explain	74. Which other positive agricultural and environmental effects have occurred in this community since 2014?	Explain

F2. Chichewa version of the key informant interview guide

Kuunika chomwe chasintha chifukwa chopanga ulimi oteteza chilengedwe ndikuchulukitsa zokolora (CSA) kuchigawo chakum'mwera kwa dziko la Malawi: Kulumikizitsa ulangizi wa zaulimi ku kasamalidwe ka chilengedwe ndi chakudya chokwanira

Community level protocol: Key Informant Interview

F.2.2.1. District code |___|___|

A2. Group Village Head (GVH) ID |___|___|___|

A3. Community name or ID |__________________|

A4. Community type (Treatment = 1, Control = 2)

A5. Interview date |___|___|___|

A6. Questionnaire number |___|___|___|

A7. Time interview started |___________|

A8. Time interview ended |___________|

A9. Interviewer name and ID __________________|

District codes

Balaka	= 01
Chikwawa	= 02
Nsanje	= 03
Thyolo	= 04
Zomba	= 05

EPA codes

Bazalie	= 0101
Livunzu	= 0201
Mitole	= 0202
Makhanga	= 0301
Zunde	= 0302
Massambajati	= 0401
Thekerani	= 0402
Thondwe	= 0501

Treatment GVH codes

Chicololere	= 010101
Kasisi	= 020101
Mparma	= 020201
Gatorma	= 030101
Mbangu	= 030201
Nkusa	= 040101
Gombe	= 040201
Mbeluwa	= 050101

Control GVH codes

Mpoto	= 010102
Chavala	= 020102
Nyambaru	= 020202
Alufazema	= 030102
David	= 030202
Mangwalala	= 040102
Chalonda	= 040202
Kutambala	= 050202

Iangizo kwa ofunsa: Dziwani kuti dera mmaphunzirowa, likuyimila mudzi kapena midzi ingapo (GVH).

Werengerani kalata yopempha chilorezo musanapitilile kucheza.

Mulibwanji, Dzina langa ndi________, ndipo ndine ochita kafukufuku yemwe ndikuimila ophunzira yemwe akuchita maphunziro apamwamba kusukulu ya ukachenjede ya Illinois ku United States of America. Tikufuna titamvetsetsa zambili za ulimi osamalira chilengedwe ndi kuchulukitsa zokolola (CSA) mu dera lanu lino. Ife sitikugwila ntchito ndi bungwe lina lililose, boma kapena chipani china chilichonse. Cholinga chathu, tikufuna timvetsetse zomwe mumachita zokhudzana ndi ulimi osamalira chilengedwe ndikuchulukitsa chakudya (CSA) m'dera lino. Ndikufuna nditacheza ndi inu ngati munthu amene mmadziwa bwino pa nkhani zomwe zimachitika m'mudzi zokhudzana ndi zaulimi komanso kasamlidwe ka chilengedwe mdera lino.

B1. Kuunika maganizo a n'dera pa zokhudza ndondomeko ya ulimi oteteza chilengedwe ndikuchulukitsa zokolola (CSA)

Funso	**Yankho**	**Funso**	**Yankho**
1. Dzina la oyankha	………………………..	2. Ndinu	i. Abambo = 1 ii. Amayi = 0
3. Dzaka	Penekelani	4. Kodi m'mudzi muno ndinu ndani? i. Amfumu =1 ii. Khansala =2 iii. Aphunzitsi =3 iv. Akulu ampingo=4 v. Ogwira ntchito kuchipatala=5 vi. Alangizi azaulimi=6 vii. Lidi farmer =8 viii. Zina = 9 (tchulani)………….. …………………………..	Tchulani

5. Mukukaniza ngati muli makomo angati m'dera lino?	i. Ochepera 20 ( ) ii. 21-50 ( ) iii. 51 – 70 ( ) iv. 71 – 100 ( ) v. Oposera 100 ( )	6. Chomwe mumadalira kwambili pamoyo wanu wa tsiku ndi tsiku mu dera lino ndichani?	Kulima = 1 Kusunga ziweto = 2 Zina (tchulani)………...... …………………………..
7. Mukuganiza kuti ndi mabanja angati m'dera lino omwe achita zinthu izi:: - Kulima mbeu = 1 - Kusunga ziweto = 2 - Kulima mbeu ndi kusunga ziweto = 3	i. Munthu m'modzi pa anthu 10 = ( ) ii. Anthu atatu pa anthu 10 = ( ) iii. Anthu 5 pa anthu 10 = ( ) iv. Anthu 7 pa anthu 10 = ( ) v. Anthu onse (100%) = ( )	8. Ndi mbewu zanji zomwe mumakonda kulima m'dera lino?	Ikani a code a mbewu
9. Kodi ndi ziweto zanji zomwe mumakonda kuweta mdera lino?	i. Ng'ombe ( ) ii. Nkhuku ( ) iii. Mbuzi ( ) iv. Nkhumba ( ) v. Zina (Tchulani)……. ..…………..…………	10. Nanga ziweto zimenezi zimawetedwa mnjira yanji mdera lino?	Mayankho: i. Kutsekulira ziweto kuti zizikadya mwazokha = 1 ii. Kuzimangilira kuti zizidya malo amodzimodzi = 2 iii. Kuzisunga mokhola =3 iv. Zina (tchulani)
11. Mu nthawi ya mvura,kodi nyengo yake imakhala yotani kwenikweni mdera lino? - Kouma kwambiri = 1 - Kouma pang'ono = 2 - Konyowa = 3 - Konyowa kwambiri = 4	Ikani ma code	12. Kodi malo ambiri mdera lino ndiooneka bwanji? - Malo ambiri ndi a fulati = 1 - Ena ndi ena ndi a fulati = 2 - Ambiri ndi okwera = 3 - Ena ndi ena ndi okwera = 4	Ikani ma code
13. Kodi dera lino liri ndima watershed?	Eya = 1 Ayi = 0, dumphani mpaka 24	14. Ngati alipo, ndima watershed angati omwe ali mdera lino?	i. 1- 3 ( ) ii. 3- 5 ( ) iii. Oposera 5 ( )

15. Pali mtunda wautali bwanji kuchoka mdera lino kufika ku watershed yoyandikira?	i. Ochepera1km = 1 ii. 1 to 5 km = 2 iii. 5 to 10km = 3	16. Ndi alimi angati mdera lino omwe amalima mozungulira watershe yi?	i. Munthu m'modzi pa anthu 10 = ( ) ii. Anthu atatu pa anthu 10 = ( ) iii. Anthu 5 pa anthu 10 = ( ) iv. Anthu 7 pa anthu 10 = ( ) v. Anthu onse (100%) = ( )
17. Pa zaka 5 zapitazi (2011-2015), Panali kusintha kulikonse kooneka pa ma khwawa (watershed) amenewa m'dera lino?	Eya = 1 Ayi = 0, dumphani mpaka 20.	18. Ngati kusintha kunalipo, ndikusintha kwanji komwe kunachitika pamakhwawa (watershed) amenewa?	Fotokozani
19. Mukuganiza ngati chinachititsa kusintha kumeneku ndi chiyani?	Fotokozani	20. Pa zaka 5 zapitazi, pali chitukuko chirichonse chomwe chinachitidwa pa khwawa liliyonse (watershed)?	Eya = 1 Ayi = 0, dumphani mpaka 24.
21. Ngati chiripo, ndichitukuko chanji chomwe chinachitidwa pama watershed wa?	1. Continuous contours (CCTs) 2. Water absorption trenches (WATs) 3. Maker ridges 4. Vetiver grass 5. Agroforestry 6. Zina (tchulani) ……………......	22. Nanga dera lanu lino linalandilapo thandizo liri lonse lokhonzera ma watershed wa?	Eya = 1 Ayi = 0 dumphani mpaka 24
23. Nanga ndi bungwe or project yanji yomwe inapeleka chithandizo chokhonzela ma watershed wa?	Dzina	24. Kodi dera lino lili ndi sikimu (scheme) yothilira mbeu?	Eya = 1 Ayi = 0, dumphani mpaka 26.

25. Nanga sikimu imeyi inabwera ndi ndani m'dera muno?	i. Ministry ya agric. …….. ii. Bungwe (tchulani)…….. …..………………... iii. Zina (tchulani) …... ..…………..............	26. Muli mlangizi wazaumi mdera lino?	Eya = 1 Ayi = 0, dumphani mpaka 31.
27. Ngati alipo, Pali ntunda wautali bwanji kuchoka mdera lino kufika komwe amakhala alangiziwa?	Ntunda mma kilomita: i. Ochepera = 1 ii. 1 to 2 = 2 iii. 2 to 5 = 3 iv. Oposera 5 = 4	28. Mongoganizira, alimi mdera lino amalandila thandizo mowirikiza bwanji kuchokera kwa alangiziwa?	i. mwapafupipafupi kwambiri ( ) ii. Mwapafupipafupi ( ) iii. Mwa kanthawi ( ) iv. Mochepera ( )
29. Ndi thandizo lanji lomwe dera lino limalandila kuchokera kwa alangiziwa?	i. Malimidwe ii. Kagwiritsidwe ntchito ka madzi iii. Kupalira iv. Kuteteza mbeu kutizilombo toononga mbeuzo v. Kusamalira umoyo wa ziweto vi. Zina (tchulani) …………………..	30. Kodi mauphungu omwe mumalandira kuchoka kwa alangiziwa mderali mungawaike pamuyeso wanji?	i. Abwino kwambiri ( ) ii. Abwino ( ) iii. Abwinoko ( ) iv. Oyesera ( ) v. oyipa ( )
31. Pa zaka 5 zapitazi, (2011-2015), pakhalako kusintha kulikonse komwe dera lino limachitira za ulimi?	Eya = 1 Ayi = 0 , dumphani mpakana 33	32. Nanga ndikusintha kwanji komwe dera lino lidachita pa zaulimi?	i. Kufupika kwa nyengo zolima ( ) ii. Kutalika kwa nyengo zolima ( ) iii. Kutalika kwambiri kwa nyengo zolima ( )
33. Kodi dera lino likudziwa za njira zamakono za ulimi wosamalira chilengedwe ndikuchulukitsa zokolora?	Eya = 1 Ayi = 0, dumphandi funso 35	34. Kodi mudadziwa bwanji za ulimi wamakono wosamalira chilengedwe ndikuchulukitsa zokolora?	WALA = 1 Zina = 0

35. Kodi dera lanu lino lidakhalako pa pologalamu ya WALA yokhudzana ndi ndondomeko zolima mu khwawa kapena mozungulira khwawa?	Eya = 1 Ayi = 0	36. Kodi ndi ndondomeko zanji zokhudza ulimi wamu khwawa (watershed) zomwe dera lanu lidalandira kuchokera ku pologalamu ya WALA?	1. CCTs ( ) 2. WATs ( ) 3. Maker ridges ( ) 4. Vetiver grass ( ) 5. Agroforestry ( ) 6. Zina (tchulani) ………….. ……………………….…...
37. Pa zaka 5 zapitazi (2011-2015) kuchokera chaka cha 2009, Ndi alimi angati mwa alimi omwe ali m'dera lino omwe adapangako ndondomeko(CCTs,WATs …) pa zaulimi wosamalira chilengedwe ndikuchulukitsa zokolora(CSA) kapena kulima mozungulira khwawa mminda yawo(watershed)?	i. Mlimi m'modzi pa alimi 10 = ( ) ii. Alimi atatu pa alimi 10 = ( ) iii. Alimi 5 pa alimi 10 = ( ) iv. Alimi 7 pa alimi 10 = ( ) v. Alimi onse (100%) = ( )	38. Kodi ndi alimi angati mwa alimi omwe ali mdera lino omwe ali ndi njira zokhudza ulimi wamakono wosamalira chilengedwe ndikuchulukitsa zokolora mminda mwawo? 1. CCTs 2. WATs 3. Maker ridges 4. Vetiver grass 5. Agroforestry 6. Zina (tchulani)	i. Mlimi m'modzi pa alimi 10 = ( ) ii. Alimi atatu pa alimi 10 = ( ) iii. Alimi 5 pa alimi 10 = ( ) iv. Alimi 7 pa alimi 10 = ( ) v. Alimi onse (100%) = ( )
39. Kodi anthu a mdera lanu lino anadziwa bwanji za njira za ulimi wamakono wosamalira chilengedwe ndikuchulukitsa zokolora mminda mwawo?	i. Potenga nawo mbali pachitukuko cha n'dera chosamalila ma khwawa(watershed) omwe adayambitsa a WALA. ii. Kuphunzilira kwa aneba. iii. Kuchokera ku bungwe lina (tchulani)	40. Kodi nkhani ya ulimi wamakono wosamalira chilengedwe ndikuchulukitsa zokolora ndiyodziwika mderali?	Eya = 1 Ayi = 0

41. Nanga mwaonako zotsatira zilizonse za ulimi umeneu mdera lino?	Eya = 1 Ayi = 0, dumphani funso 43.	42. Ngati mwazionako, kodi ndizotsatira zanji kokhudzana za ulimi wosamalira chilengedwe ndikuchulukitsa zokolora?	Kuchepetsedwa kwa madzi othamanga a mvura = 1 Zokolola zochuluka = 2 Zina = 0
43. Pa zaka 5 zapitazi (2011-2015), kodi alimi mdera lino anaonako kusintha pa zokolola za chimanga?	Eya = 1 Ayi = 0	44. Nanga zaka ziwiri zapitazi (2013-2014), kodi alimi mdera lino anaonako kusintha pa zokolola za chimanga?	Eya= 1 Ayi = 0
45. Pa zaka 5 zapitazi (2011-2015), ndi chimanga chochuluka bwanji chomwe chinakoloredwa pa hectare mdera lino? (mmatumba a 50kg)	i. 0 to 10 ( ) ii. 11 to 20 ( ) iii. Oposera 20 ( )	46 Pa zaka zitatu zapitazi (2012-2013), ndi chimanga chochuluka bwanji chomwe chinakoloredwa pa hectare mdera lino? (mmatumba a 50kg)	i. 0 to 10 ( ) ii. 11 to 20 ( ) iii. Oposera 20 ( )
47. Pa zaka ziwiri zapitazi (2013-2014), ndi chimanga chochuluka bwanji chomwe chinakoloredwa pa hectare mdera lino? (mmatumba a 50kg)	i. 0 to 10 ( ) ii. 11 to 20 ( ) iii. Oposera 20 ( )	48. Nanga chaka chapitachi zapitazi (2014), ndi chimanga chochuluka bwanji chomwe chinakoloredwa pa hectare mdera lino? (mmatumba a 50kg)	i. 0 to 10 ( ) ii. 11 to 20 ( ) iii. Oposera 20 ( )
49. Kuchokela pachiyambi cha WALA project n'chaka cha 2009 mpakana pano, pali kusintha kulikonse kwa dothi mdera lino?	Eya = 1 Ayi = 0, dumphani funso 51.	50. Ngati pali kusintha, ndikusintha kwanji komwe kwachitika pa dothi la mdera lino?	i. Kupezeka kwa chinyontho mu nthaka kamba ka kuchepa kwa madzi othamanga - Kuchuluka kwa madzi a mvula olowa mu nthaka - Kupezeka kwa manyowa abwino pamwamba pa nthaka - Zina (tchulani)

51. Pa zaka ziwiri zapitazi, (2013/2014), pachitikako kusintha kulikonse pakapezedwe ka chuma kwa alimi a mdera lino?	Eya = 1 Ayi = 0, skip to 51	52. Ngati kusintha kulipo, ndikusintha kwachuma kotani komwe alimi a m'dera lino anakupeza?	i. Ndalama zochuluka zochokera ku ulimi ( ) ii. Chakudya chochuluka iii. Umoyo wabwino ( ) iv. Kuchuluka kwa ana mmasukulu ( ) v. Zina (tchulani)………….. …………………………..
53. Ndi alimi angati mwa alimi omwe ali m'dera lino omwe anawona kusintha kwa chuma chawo kuchokera n'chaka cha 2014?	i. Mlimi m'modzi pa alimi 10 = ( ) ii. Alimi atatu pa alimi 10 = ( ) iii. Alimi 5 pa alimi 10 = ( ) iv. Alimi 7 pa alimi 10 = ( ) v. Alimi onse (100%) = ( )	54. Ndi alimi angati mwa alimi omwe ali m'dera lino omwe sanawone kusintha kwa chuma chawo kuchokera n'chaka cha 2014?	i. Mlimi m'modzi pa alimi 10 = ( ) ii. Alimi atatu pa alimi 10 = ( ) iii. Alimi 5 pa alimi 10 = ( ) iv. Alimi 7 pa alimi 10 = ( ) v. Alimi onse (100%) = ( )
55. Kwa alimi omwe sanaone kusintha pa chuma chawo, mukuganiza kuti ndichifukwa chani chomwe chidapangitsa kuti chuma chawo chisasinthe m'dera lino?	1. Chifukwa cha kusintha kwa nyengo 2. Kuchepa kwa njira zomwe zinaikidwa pokhonzekera ngozi zakudza kamba kwakusintha kwa nyengo 3. Chifukwa chakudwala 4. Zina (tchulani)……………… ………………………..	56. Ndi zinthu zina ziti zomwe mumaziona zofunikira pa zaulimi ndi chuma pa umoyo wa anthu a m'dera lino?	i. The landscape ii. Mtunda ochokera ku ma tauni iii. Umoyo wa anthu a m'dera lino iv. Zina (tchulani)………………… ……………………………..

57. mzaka 5 zapitazi kuchoka chaka cha 2011, dera lanu lino lidaphunzitsidwako zakakhozekeredwe ka ngozi zokudza kamba kakusintha kwa nyengo? (monga envtal shocks ndi ulimi osamalira chilengedwe ndikuchulukitsa zokolora?	Eya = 1 Ayi = 0, dumphani mpaka 61.	58. Ngati lidaphunzitsidwako, dera lanu lidaphunzitsidwa zinthu zotani zakukhonzekera ngozi zimenezi zakudza kamba kakusintha kwa nyengo?	Tchulani
59. Ndi bungwe liti lomwe lidapeleka maphinziro okhonzekera ngozi zokudza kamba ka kusintha kwa nyengo?	Tchulani	60. Kodi maphunziro omwe mudaphunzira okhudza kukhonzekera kwa ngozi zokudza kamba kwakusintha kwa nyemgo, komaso ulimi osamalira chilengedwe ndikuchulukitsa chakudya mutha kuwaika pa muyeso wanji?	i. Okwanira ii. Okwanira pang'ono iii. osakwanira
61. Muli mtsinje uliwonse m'dera lino?	Eya = 1 Ayi = 0	62.Tchulani dzina ndi nambala yamitsinje yomwe ili m'dera lino	<u>Nambala ya mitsinje</u>
63. Kwenikweni mitsinje imeneyi ndiyozama bwanji?	Yolekeza i. Mmapazi ( ) ii. M'mawondo ( ) iii. munchiuno ( ) iv. mmapewa ( ) v. Opitilira msinkhu wa munthu ( )	64. Kodi pakali pano, mtsinje umenewu ndiozama bwanji?	Olekeza i. Mmapazi ( ) ii. M'mawondo ( ) iii. munchiuno ( ) iv. mmapewa ( ) v. Opitilira msinkhu wa munthu ( )

65. Mu nchaka cha 2015 mtsinje umenewu unali ozama bwanji?	Olekeza i. Mmapazi ( ) ii. M'mawondo ( ) iii. munchiuno ( ) iv. mmapewa ( ) v. Opitilira msinkhu wa munthu ( )	66. Mu nchaka cha 2014 mtsinje umenewu unali ozama bwanji?	Olekeza i. Mmapazi ( ) ii. M'mawondo ( ) iii. munchiuno ( ) iv. mmapewa ( ) v. Opitilira msinkhu wa munthu ( )
67. Mu nchaka cha 2013 mtsinje umenewu unali ozama bwanji?	Olekeza i. Mmapazi ( ) ii. M'mawondo ( ) iii. munchiuno ( ) iv. mmapewa ( ) v. Opitilira msinkhu wa munthu ( )	68. N'chaka cha pakati pa 2009 ndi 2012, mtsinje umenewu unali ozama bwanji?	Olekeza i. Mmapazi ( ) ii. M'mawondo ( ) iii. munchiuno ( ) iv. mmapewa ( ) v. Opitilira msinkhu wa munthu ( )
69. Kodi Munaonako kusintha kulikonse pakachulukidwe ka madzi ogwiritsa ntchito m'dera lanu lino chiyambileni kutenga nawo mbali pa zokasamalidwe ka makhwawa (watershed) omwe aWALA adakhazikitsa?	Eya = 1 Ayi = 0	70. Ndikusintha kwanji komwe komwe mwakuwona?	Fotokozani
71. Mukuganiza ngati ndi chiyani chachititsa kusintha kumeneku?	Fotokozani	72. Ndi anthu angati mwa anthu a m'dera lino omwe amapeza madzi aukhondo mosavuta kuchokera n'chaka cha 2014?	i. Munthu m'modzi pa anthu 10 = ( ) ii. Munthu m'modzi pa anthu 10 = ( ) iii. Munthu m'modzi pa anthu 10 = ( ) iv. Munthu m'modzi pa anthu 10 = ( ) v. Anthu onse (100%) = ( )

73. Pelekani chifukwa	Fotokozani	74. Mwazotsatira zina, ndi zotsatira zina zabwino zanji za ulimi komaso chilengedwe zomwe zachitika m’dera lino kuchokera n’chaka cha 2014?	Fotokozani